The passive representations were consciously formed via the representational transition from the active state

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Abstract

The passive state serves robust maintenance for memory representations, which perform a functionally different role from the active state during multistate maintenance in visual working memory. However, it is still unclear how passive representations are formed. The current study was based on embedded process models and activity-silent models to explore this question by adopting a sequential presentation paradigm. We mainly modulated the presentation time of subsequent stimuli and the retention interval between the two memory arrays. These results demonstrated that passive representation was consciously formed via the representational transition from the active state, rather than in a spontaneous manner during the memory encoding period; moreover, the representational transition was driven by cognitive demands. The current study presented insights into the contribution of passive maintenance to long-term memory.

Keywords: working memory, passive representation, representational transition, active state, cognitive demands

Introduction

Visual working memory (VWM) is responsible for temporary retention and online manipulation of visual information from the external environment for high-level cognition (Aben et al., 2012; Baddeley, 1992; Baddeley & Hitch, 1974; LaRocque et al., 2015). Different from the static scenario, where all memory items were putatively retained in a single memory state, more work has evidenced that the hierarchy of working memory was often thought to comprise at least two states: the active and passive states (Nee & Jonides, 2013; Oberauer, 2002; Oberauer & Lange, 2009). The representational state of memory items flexibly switches according to the cognitive demands of tasks.

The active state is tightly related to ongoing processing; memory maintenance in the active state is assumed to depend critically on persistent neural activity (Kamiński & Rutishauser, 2020; Manohar et al., 2019; Stokes, 2015). Notably, memory can be well maintained in the passive state over a short delay with the absence of sustained neural activity that tracks that memory (LaRocque et al., 2013; Lewis-Peacock et al., 2012a; Stokes, 2015). Proponents of passive maintenance argued that memory representations are effectively maintained through weight-based changes in synaptic connectivity (Mongillo et al., 2008; Muhle-Karbe et al., 2021; Stokes, 2015). In contrast to active representations, passive representations are temporarily irrelevant to ongoing processing and exert little influence. Accumulating evidence has demonstrated that passive representations are robust and resistant to interference and time decay (Johanna Kreither, 2021; Stokes et al., 2020; Zhang et al., 2021).

Importantly, passive representations need to be reformatted into active representations that allow them to guide behavior when needed (Stokes, 2015; Stokes et al., 2020). The view that memory representations are dynamic and modifiable via cognitive control has been supported by the observation of a reactivation effect of passive representations following the application of an impulse stimulus or transcranial magnetic stimulation (TMS) to the target brain cortex (Rose et al., 2016; Widhalm & Rose, 2019; Wolff et al., 2015, 2017). Previous research has behaviorally evidenced a resource-dissociation account, which indicated that active load variation had no effect on passive memory performance and vice versa (Li et al., 2021; Oberauer, 2002).

The state-based theory of working memory has been supported by embedded process models and activity-silent models, which elucidated the representational state from the perspective of functional roles and neurophysiological mechanisms, respectively. The two theoretical models present different views on the source of passive representations. Embedded process models propose that memory representation exists in one of the two states. When attention subsequently shifts to other information, the memory representation that was previously in the active state drops its active format and transitions to the passive state (LaRocque et al., 2014). Hence, passive representations are assumed to consciously form via a representational transition from the active state according to task demands. The activity-silent models argue that the passive format of memory representation emerges accompanying its active format for the memory item encoded into VWM, because the activity during encoding temporarily changes synaptic efficacy within the neural network. The

passive format of prospective representations still exists following the drop of the active format when attention shifts towards other items. Thus, the passive representation is supposed to spontaneously form once the sensory stimulus has been encoded into the VWM. However, there is a rare study to empirically explore how passive representation forms during multistate maintenance.

Notably, that issue motivates us to examine whether there is a representational transition when memory representation drops its activity format. According to the two hypotheses mentioned above, the transition process would occur to obtain passive maintenance if the passive representations were consciously formed, whereas if the passive representation formed spontaneously, the drop of the active format indicated the attenuation of neural activity, thus without the engagement of representational transition.

Prior research provided us with an effective experimental paradigm to distinguish whether the drop of representations' active format accompanied with the representational transition or the activity attenuation (Zhang et al., 2021). In Zhang et al.'s research, participants were instructed to successively encode two sets of memory items and retrieve them separately. The electroencephalograpy (EEG) recordings indicated that the first set was retained in the passive state during the active processing of the second set. Their behavioral result pattern was incompatible with the resource-dissociation account by showing an effect of the active load variation on the passive representations. This incompatibility presumably implies that the memory representations presented first had not dropped the active format yet when the

subsequent stimuli appeared. The representational transition account presumed that such a short presentation time (200 ms) of subsequent stimuli caused an overlap between the transition process and the sensory processing of subsequent stimuli and thus impeded a smooth transition. In such a case, a relatively long presentation would allow the transition process to precede the subsequent sensory processing, thereby eliminating the effect of active load variation on passive representations. However, considering the activity attenuation account, the memory representations without the drop of active format were presumed to be definitely interfered by subsequent stimuli, since the sensory processing of the new stimuli elicited neural activation in the primary visual cortex. The passive format underlying the memory representations was affected correspondingly. If so, that effect on the passive representations would be observed, regardless of the presentation time of subsequent stimuli.

Therefore, the current study aimed to investigate whether the drop of the active format of memory representations accompanied by representational transition, which could account for how the passive representations formed. We adopted a sequential presentation task modeled after Zhang et al.'s (2021). First, the presentation of subsequent stimuli was modulated in Experiment 1, where the short and long presentations randomly appeared within each block. Unfortunately, the results failed to provide convincing evidence for either of the proposed hypotheses, which was presumed to be contaminated by the unpredictability of temporary context. Furthermore, the presentation of subsequent stimuli was kept constant within each block in Experiment 2. The results denied the activity attenuation account and

evidenced a representational transition to the passive state following the drop of the active format. Then, the delay retention between the two arrays was modulated in Experiment 3, and the results further evidenced the representational transition for passive maintenance, which also revealed that the transition process was driven by cognitive demands. Overall, these results demonstrated that the passive representation was consciously formed via the representational transition from the active state according to the cognitive demands.

Experiment 1

Experiment 1 aimed to explore whether the representational transition occurred when the memory representation temporarily dropped its active format. In the current sequential presentation tasks, the experimental parameters were based on Zhang et al.'s. We selected 200 ms vs. 500 ms as the short and long presentations of subsequent stimuli to test our hypotheses; the short and long presentation times randomly appeared within each block. We predicted that if there was a representational transition to the passive state following the drop of active format of memory representations, the effect of active load variation on the passive performance would not be observed in the relatively long presentation condition, while the effect would be unrelated to the presentation time if the drop of active format indicated the activity attenuation.

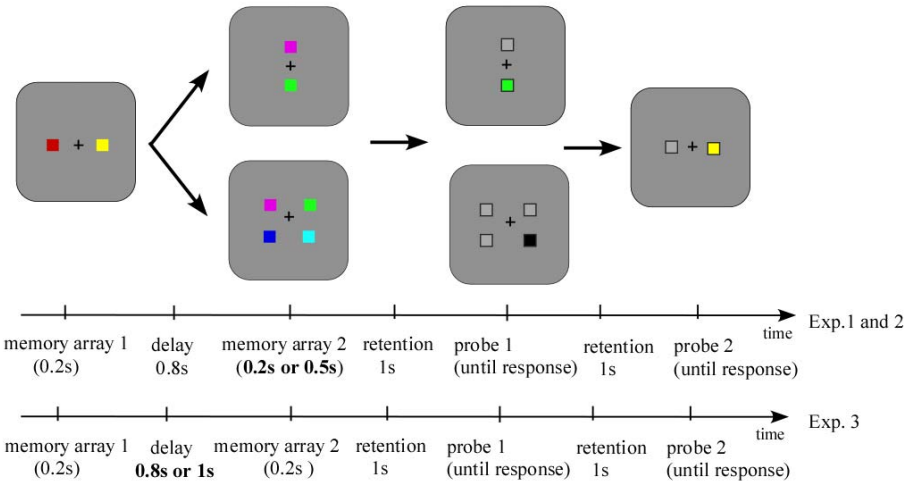


Figure 1: A schematic diagram of the task in Experiments 1, 2, and 3. Participants were instructed to remember all the colored squares in the two memory arrays. There are consistently two items in memory array 1. Memory array 2 presents two items in the low-load condition and four items in the high-load condition. The items in memory array 2 were detected by probe 1, while the items in memory array 1 were detected by probe 2. The values below the boxes indicate the time interval.

Methods

Participants

Sample size determination was based on a previous study that indicated the magnitude of the effect could be expected (Li et al., 2021). We used a similar sample size (30 in each experiment) to ensure that the findings were reliable. None of the participants overlapped across the experiments. Thirty normal college students (5 males; mean age: 21.13 ± 2.39 years) participated voluntarily in Experiment 1. All participants signed informed consent forms prior to participation. They reported

normal or corrected-to-normal visual acuity, as well as normal color vision. All experiments were carried out in accordance with the Declaration of Helsinki. The study was approved by the Human Research Institutional Review Board at Liaoning Normal University.

Apparatus and stimuli

All stimuli were presented against a gray background on a 19-inch LCD monitor (60-Hz refresh rate, 1920 × 1080 pixels). The experimental program was conducted using E-Prime 2.0 software. Responses were made using a computer keyboard. Memory stimuli were colored squares (0.49° × 0.49°) that were independently selected from eight discriminable colors (blue, black, red, magenta, lime, purple, yellow, and cyan) without replacement within a trial. Each color stimulus was located on an invisible square (1.80° × 1.80°) around a fixation cross (0.23°) that was positioned in the center of the screen and was constantly visible throughout the trial. Two colored squares were presented above and below the fixation cross in memory array 1. In memory array 2, two colored squares were presented left and right of the fixation cross or four squares located at the vertices of that invisible square. The memory display was designed such that the positions of the memory stimuli were not perceptually overwritten. Participants adjusted their seats so that their eyes were level with the center of the screen before the beginning of the trials. They were seated at a viewing distance of 70 cm in a chamber.

Procedure

The schematic of Experiment 1 is depicted in Figure 1. Each trial was started with just the fixation cross present on the screen for 500 ms. Memory array 1 was then presented for 200 ms. Following a delay of 800 ms, memory array 2 was presented with two items in the low-load condition and with four items in the high-load condition. The presentation time (200 ms vs. 500 ms) of memory array 2 randomly varied in each block. Memory arrays 1 and 2 were presented sequentially and detected in reverse order. After the disappearance of memory array 2 and a 1000 ms delay, the probe arrays appeared sequentially. One of these squares, with a black border in each probe array, was colored. These squares in probes 1 and 2 were congruent with the memory items of memory arrays 2 and 1, correspondingly in number and spatial locations. During the detection phase, participants were instructed to decide whether the color of the items in probe 1 was identical to that of items located in the corresponding position in memory array 2, and they were given a similar instruction for probe 2, which corresponded to memory array 1. The manner of encoding and detection encouraged participants to retain memory arrays 1 and 2 in the passive and active states, respectively. That is, memory array 1 dropped the active format when encoding memory array 2. The probe arrays did not disappear until a response was given. In half of the trials, the colors of the probe items were identical to those of the memory items, and the participants were instructed to press *Z* in that case. In the remaining trials, the probe items had new colors within a trial, and the response was made by pressing *M*. The identical and nonidentical trials for the two probe arrays were randomly presented, with a 50% probability of appearing each time.

The participants were required to perform six blocks, consisting of 192 trials in total. The variables of presentation time and load were mixed within each block. We ensured that the participants understood the procedure clearly by providing appropriate instruction and a practice session of eight trials. Feedback was given in the practice trials, but not in the formal trials. Participants were encouraged to remember the two sequential arrays in a separate manner. They should have aimed to be accurate over being as fast as possible. Before the beginning of each block, a four-digit number that varied between blocks was presented. The participants were asked to subvocally recite the numbers to prevent speech from encoding the visual information (Shaffer & Shiffrin, 1972).

The data were analyzed using JASP software (Love et al., 2019). The effect size of the analyses of ANOVA is reported as $\eta^2 p$. For the t-test concerning the load effect on memory performance in the two storage states, effect sizes (Cohen's d) were calculated. We also report Bayes factors quantifying the evidence for the alternative over the null hypothesis (Schmalz et al., 2021).

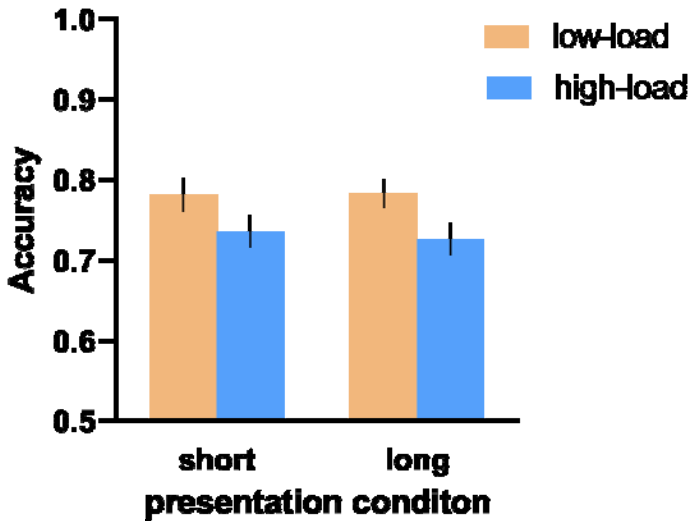


Figure 2: Mean accuracy in the passive state in Experiment 1. Error bars indicate the standard error.

Results

The accuracy data were the main dependent measure. Probe 1 indicated memory performance in the active state, while probe 2 indicated memory performance in the passive state. We conducted an ANOVA using the variables of load (low-load vs. high-load) and presentation time (200 ms vs. 500 ms) for the accuracy of passive representations. As depicted in Figure 2, a significant main effect of load was detected (F (1, 29) = 16.335, $p < 0.001$, $\eta^2 p = 0.360$), but the interaction between load and presentation time was not statistically significant (F < 1). The results suggested that the active load variation influenced the passive representations in both the short and long presentation conditions. The results pattern in the short presentation condition replicated the results of Zhang et al.'s; importantly, extending the presentation of

subsequent stimuli did not eliminate the effect of active processing on the passive representations.

Discussion

The results seemingly provided support for the activity attenuation account by showing that the effect of active load variation on the passive representations was independent of the presentation of subsequent stimuli. However, it should be noted that the unpredictability of the temporal context might prompt participants to urgently initiate subsequent active processing. Thus, the current results pattern could not rule out the possibility that the representational transition still overlapped with subsequent active processing even in the long presentation condition due to the unpredictability of the temporal context. Therefore, we attempted to rescue temporal predictability to further explore whether the drop of the active format conformed to the representational transition account or the activity attenuation account in the following experiment.

Experiment 2

We further explored whether the drop of the active format of memory representations accompanied with representational transition in Experiment 2, aiming to convincingly demonstrate how the passive representations formed. Unlike Experiment 1, the presentation of subsequent stimuli (200 ms vs. 500 ms) was in block design to keep the temporal context constant in each block. We put forth a similar prediction to Experiment 1.

Methods

Participants

Thirty neurologically normal college students (6 males; mean age: 22.07 ± 2.22 years) were recruited for this experiment. All participants signed informed consent forms prior to participation. They all reported normal or corrected-to-normal visual acuity, as well as normal color vision.

Stimuli and procedure

All materials and the procedure employed in Experiment 2 were the same as in Experiment 1, except for the following (see Figure 1). The presentation time (200 ms vs. 500 ms) of memory array 2 was modulated in the block design. In this part, participants were required to perform the short and long presentation conditions with 5 blocks each, consisting of 320 trials in total. The order of the presentation condition was counterbalanced between the subjects. The low-and high-loads were randomly presented in each block with equal probability. To ensure that the participants understood the procedure clearly, they were presented with appropriate instruction and a practice session of eight trials for each of the short and long presentation conditions.

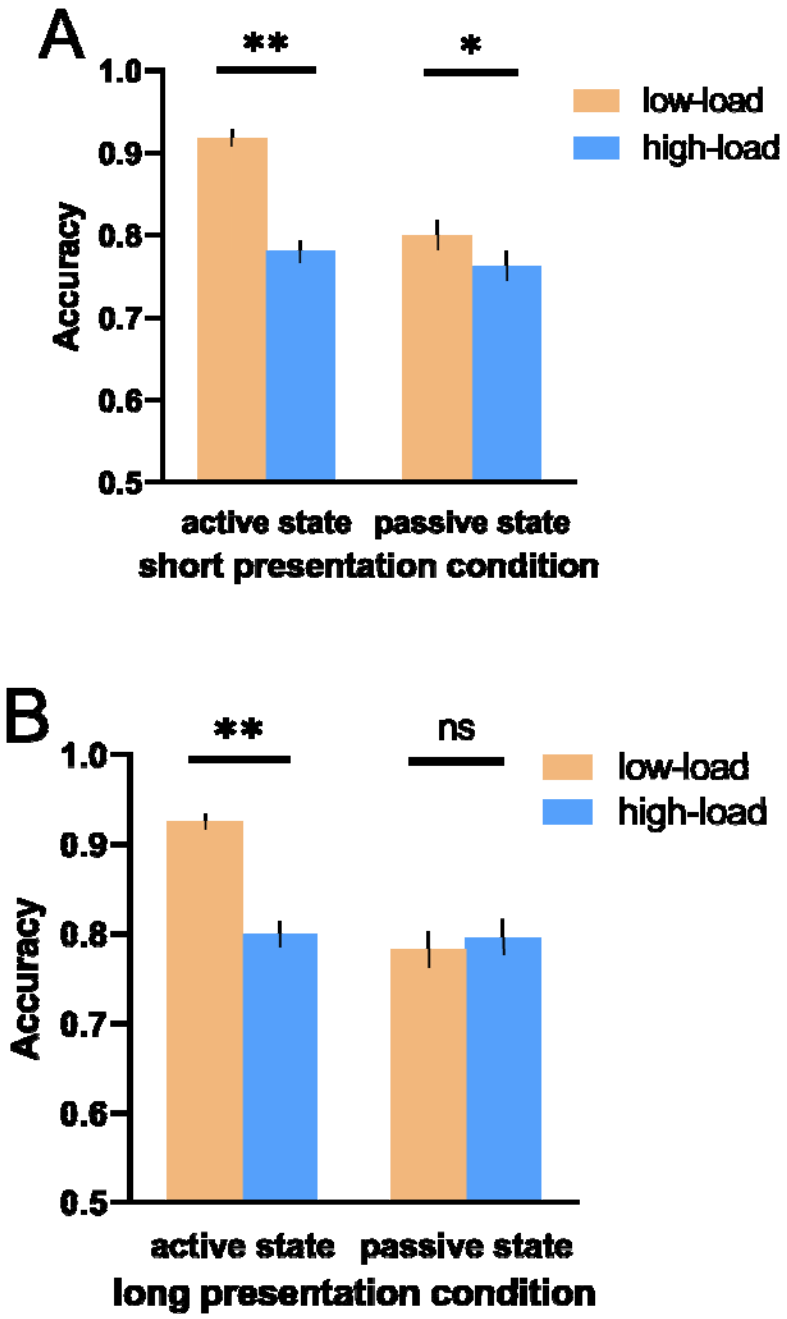


Figure 3: Mean accuracy in the active and passive states in the short presentation condition (A) and the long presentation condition (B) in Experiment 2. Error bars indicate the standard error.

Results

A traditional data analysis was conducted via a repeated measures analysis of variance (ANOVA) using the variables load (low-load vs. high-load), storage state (active state vs. passive state), and presentation time (200 ms vs. 500 ms). The 2 × 2 × 2 ANOVA revealed a significant interaction between presentation time and load (F (1, 29) = 8.229, p = 0.008, η^2p = 0.221), and the interaction between storage state and load (F (1, 29) = 81.676, p < 0.001, η^2p = 0.738). The participants' accuracy depending on the short and long presentation conditions was then analyzed and depicted in Figure 3.

For the short presentation condition (Figure 3A), accuracy data were analyzed by a 2 (low-load vs. high-load) × 2 (active state vs. passive) ANOVA. We detected a significant interaction between load and storage state (F (1, 29) = 35.603, p < 0.001, η^2p = 0.551), which was driven by a greater accuracy decrease for the active state relative to the passive state. A test of the simple effect showed that, for the active state, the accuracy was significantly higher in the low-load condition than in the high-load condition, t(29) = 14.699, p < 0.001, Cohen's d = 2.684, BF_{10} = 1.115e+12. Similarly, the participants' accuracy was also significantly higher in the low-load condition than in the high-load condition in the passive state, t(29) = 3.658, p = 0.001, Cohen's d = 0.668, BF_{10} = 32.991. These results showed an effect of active load variation on passive representations, which replicated previous results.

In the long presentation condition (Figure 3B), we conducted a similar 2 × 2 ANOVA as in the short presentation condition. A significant interaction was evident between load and storage state (F (1, 29) = 62.279, p < 0.001, η^2p = 0.682). This was

driven by a lack of load effect in the passive state. The test of a simple effect showed that, for the active state, the accuracy was significantly higher in the low-load condition than in the high-load condition, $t(29) = 8.846$, $p < 0.001$, Cohen's $d = 1.615$, $BF_{10} = 1.148e+7$. However, for the passive state, the participants' accuracy was not significantly different between the low-load and high-load conditions, $t(29) = 1.121$, $p = 0.272$, Cohen's $d = 0.205$, $BF_{10} = 0.344$. These results suggest that there was no effect of active load variation on the passive representations in the long presentation of subsequent stimuli, which showed a different result pattern from the short presentation condition.

Discussion

These results suggest that the sufficient presentation of subsequent stimuli removed the effect of active load variation on passive memory when the temporal context was not beyond participants' predictability. According to the logic of the current research, we interpreted the findings as evidencing that dropping the active format of memory representations led to a representational transition to the passive state. Also, the current findings reconciled with Zhang et al.'s results by suggesting that the observed effect was caused by the insufficient presentation time of subsequent stimuli, because the insufficiency led to an overlap of representational transition with subsequent active processing. Overall, the results of Experiment 2 demonstrated that passive representation was consciously formed via the representational transition from the active state, which denied the spontaneity of passive representations. Based on the proposal of representation transition following the drop of active format, we

hypothesized that the transition would not continue to the presentation of subsequent stimuli when the delay retention was sufficiently long. That was testified in the following experiment.

Experiment 3

The aim of Experiment 3 was to further evidence the representational transition account. In the previous two experiments, where the delay retention was fixed at 800 ms, we presumed that the delay retention might be insufficient for the representational transition, and thus the transition process continued during the presentation of subsequent stimuli and overlapped with sensory processing. In terms of the representational transition account, we expected that the representational transition would be complete before the presentation of subsequent stimuli when providing a sufficiently long delay. If so, we predicted that there was no effect of active load variation on the passive representations by extending the delay retention. We selected 800 ms vs. 1000 ms as the delay retention to test this hypothesis.

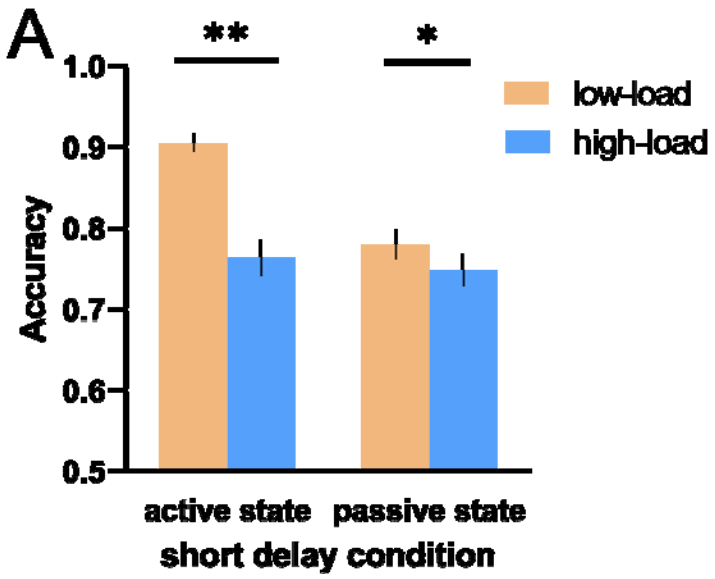
Methods

Participants

Thirty neurologically normal college students (5 males; mean age: 21.97 ± 2.70 years) were recruited for this experiment. All participants signed informed consent forms prior to participation. They all reported normal or corrected-to-normal visual acuity, as well as normal color vision.

Stimuli and procedure

All materials and the procedure employed in Experiment 3 were the same as in Experiment 1, except for the following (see Figure 1). The presentation time of memory array 2 was fixed at 200 ms. The delay retention between the two memory arrays lasted 800 ms in the short delay condition and 1000 ms in the long delay condition. The effect of delay retention was assessed in the block design. In this part, participants were required to perform the short and long delay conditions with five blocks each, consisting of 320 trials in total. The order of the delay condition was counterbalanced between the subjects. The low-and high-load were randomly presented in each block with equal probability.



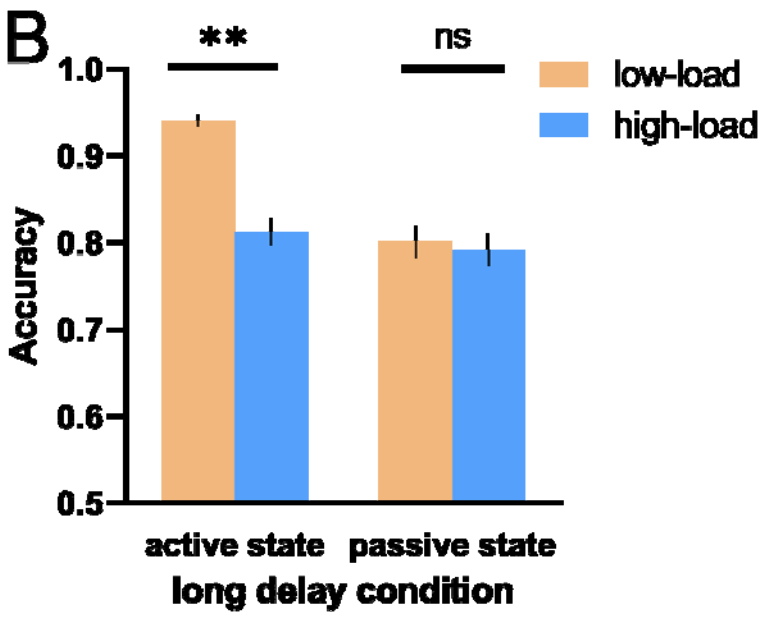


Figure 4: Mean accuracy of the active and passive states in short (A) and long (B) delay conditions in Experiment 3. Error bars indicate the standard error.

Results

The data across all participants were subject to the same analysis plan as in Experiment 1. A 2 (low-load vs. high-load) × 2 (active state vs. passive state) × 2 (800 ms vs. 1000 ms) ANOVA revealed a statistically significant interaction between storage state and load (F (1, 29) = 45.259, $p < 0.001$, $\eta^2p = 0.609$). We then analyzed the behavioral accuracy by conducting a 2 (low-load vs. high-load) × 2 (active state vs. passive state) ANOVA for the short and long delay conditions. As shown in Figure 4A, in the short delay condition, there was a statistically significant interaction between load and storage state (F (1, 29) = 17.522, $p < 0.001$, $\eta^2p = 0.377$), which was driven by a smaller decrease of accuracy in the passive state. Subsequent analysis of the simple effect suggested that, for the active state, the accuracy was much higher in the

low-load condition than in the high-load condition, $t(29) = 6.749$, $p < 0.001$, Cohen's $d = 1.232$, $BF_{10} = 75595.299$. Likewise, for the passive state, the accuracy was significantly higher in the low-load condition than in the high-load condition, $t(29) = 3.044$, $p = 0.005$, Cohen's $d = 0.556$, $BF_{10} = 8.249$. The results pattern replicated those in previous experiments, showing an effect of active load variation on the passive representations.

An important analysis of the long delay condition was conducted. Figure 4B shows a significant interaction between storage state and load (F (1, 29) = 36.239, $p < 0.001$, $\eta^2 p = 0.555$). The interaction was driven by the null effect of active load variation on passive representations. We then conducted an analysis of the simple effect. For the active state, the accuracy was significantly higher in the low-load condition than in the high-load condition, $t(29) = 8.682$, $p < 0.001$, Cohen's $d = 1.585$, BF_{10}= 7.879e+6. However, for the passive state, the accuracy was comparable in both the low-load and the high-load conditions, $t(29) = 0.813$, $p = 0.423$, Cohen's $d = 0.148$, $BF_{10} = 0.263$. The results showed no effect of subsequent active processing on passive representations in the long delay condition. We presumed that the short delay was one of the sources of the overlap between the representational transition and subsequent sensory processing.

Discussion

These results suggest that the representational transition was smoothly completed during the delay retention by extending the delay retention between the two arrays so

that there was never an overlap during the presentation of subsequent stimuli. Hence, these findings have further confirmed the transition process to the passive state but also elucidated that the representational transition was driven by cognitive demands rather than new stimuli.

General discussion

The aim of the current study was to explore how passive representations are formed during the multistate maintenance of VWM. To this end, we adopted a sequential presentation paradigm to identify whether there was a representational transition when the active format of the memory representation was dropped. The results in Experiment 1, where the short and long presentation of subsequent stimuli randomly appeared within each block, failed to convincingly testify to this issue. To rule out the effect of the unpredictability of the temporal context, the short and long presentation of subsequent stimuli was in block design in Experiment 2. The results provided evidence for the representational transition account, which proposed that passive representations were consciously formed via a representational transition. Experiment 3 modulated the delay retention between the two arrays and further demonstrated the representational transition for passive maintenance, additionally revealing that the transition process was driven by cognitive demands. Overall, we concluded that passive representation was consciously formed via a representational transition from the active state according to the task demands.

The current results, in fact, fall in line with the resources-dissociation account

of VWM (Li et al., 2021; Oberauer, 2002). Notably, the time frame for stimulus events played a critical role in the multistate maintenance of the VWM system. That is, a sufficient time space should be secured to make the representational transition to the passive state precede the subsequent active processing so that the prospectively relevant representations can be perfectly independent from the ongoing processing. This motivated us to conclude that a perfect state switch of memory items involved two kinds of time-related factors: one was sufficient blank retention that acted as the premise for state transition (LaRocque et al., 2013; Li et al., 2020; Oberauer, 2001, 2005); the other was an appropriate period reserved for a representational transition to the passive state during either the delay retention or the presentation of sensory stimuli.

The activity-silent model of VWM depicted a dynamic coding framework for working memory maintenance from a neuropsychological perspective. Regarding the source of passive representation, the activity-silent model presumed that the passive format of memory representations accompanied their active format when sensory stimuli were initially encoded into the VWM; however, the current findings were incompatible with this model by showing that the passive representation derived from the representational transition from the active state. The current study might promote a slight modification of the activity-silent model in terms of the relation between active and passive maintenance. Since the pattern of short-term synaptic plasticity underlies both passive maintenance and long-term memory maintenance, the transition manner for passive representations has the implication that handing off

memory representations into the passive state benefits their maintenance in long-term memory (LaRocque et al., 2013; Lewis-Peacock et al., 2012b; McCabe, 2008; Rose et al., 2014). From this perspective, the act of transferring the memory representations into the passive state for passive maintenance provided us with enlightenment about optimizing long-term memory maintenance in mind.

In the current study, we proposed that the state transformation of memory representations unfolds over time. This was consistent with the neural activity of EEG recordings, which showed that the time required for memory representations to fall to the baseline level was roughly 1.25 s, and with the time estimate for offloading the memory items into the passive state from behavioral studies (LaRocque et al., 2013; Oberauer, 2001, 2005). However, the time available for the formation of passive representations was never isolated from the time span estimated for state transformation in previous studies. In terms of interference with prospectively relevant representations from subsequent active processing, we found that the cognitive resources for the representational transition were conceivably not domain-specific but shared with sensory consolidation of new stimuli into the active state (LaRocque et al., 2013). Also, the passive representations could smoothly form before or after the subsequent stimuli presentation, which indicated that the state transition of memory representations was not necessarily triggered by new stimuli but possibly by cognitive demands. Also, the memory representations transitioned to the passive state in a strategic manner, according to the task context. In conclusion, these findings have shown that passive representations are consciously formed via a

top-down process.

Conclusion

In summary, passive representations are consciously formed via a transition process from the active to the passive state. The current results imply that, at the neural level, the active format of memory representation does not accompany a pattern of synaptic weights for its passive maintenance. We have concluded that transferring memory representations into the passive state for short-term maintenance contributes to the synaptic pattern, which underlays the memory maintenance of the passive state and long-term memory. This perspective inspired us to propose that the passive maintenance of memory representations could boost their performance in long-term memory.

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Declarations of interest: none.

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