The pattern of passive representations derives from the transformation of active representations in working memory

Abstract

Visual working memory system acts as the cornerstone of high-level cognition. The state-based models of working memory delineated a hierarchy of functional states, whereby the passive representations gained a robust maintenance during the concurrent processing of active representations. The passive representations have been generally recognized as a critical pattern of memory maintenance. However, it was still unclear how the passive representations were patterned. The embedded process models proposed that the passive representations were viewed as the product of transforming active representations. While the activity-silent model argued that the passive representations derived from the perceptual representations of memory stimuli, due to the passive state coexisting with the activity state of memory representations. The contradiction between the two accounts lied in whether a transition process was involved in the formation of passive representations. To explore this question, we adopted a sequential presentation task which effectively dissociated the storage state of memory representations, where the presentation time and delay interval between memory arrays were modulated. These results suggested that the formation of passive representations involved a transition process. Therefore, we concluded that the pattern of passive representations derived from the transformation of active representations. These findings will deepen the understanding of the neural mechanisms of passive

state, and provide further step toward exploring the multi-state maintenance of visual working memory.

Key words: visual working memory, sequential presentation task, passive representations, transition process, active representations, transformation

1 Introduction

Visual working memory (VWM) is responsible for temporary retention and online manipulation of visual information for high-level cognition (Aben et al., 2012; Baddeley, 1992; Baddeley & Hitch, 1974; LaRocque et al., 2015). Previous study has focused on the exploration of working memory maintenance with a single state, which was conceptually equivalent to the active state (Todd & Marois, 2004; Vogel & Machizawa, 2004; W. Zhang & Luck, 2008). However, the passive state has been generally recognized as a critical pattern of representational maintenance, which complemented the active maintenance of WM (Chota & van der Stigchel, 2021; Nee & Jonides, 2013; Oberauer, 2002). Different from the active representations which depend critically on persistent neural activity (LaRocque et al., 2013; Lewis-Peacock et al., 2012; Johanna Kreither et al., 2022), the passive representations are effectively maintained through weight-based changes in synaptic connectivity, thus no detection of sustained activity (Mongillo et al., 2008; Muhle-Karbe et al., 2021; Oberauer & Awh, 2022; Stokes et al., 2020). The lingering synaptic trace of passive representations could be revealed by the reactivation effect following the application of an impulse visual stimulus or transcranial magnetic stimulation to the target brain cortex (Rose et al., 2016; Wolff et al., 2015, 2017). The passive representations are currently irrelevant to the task but conferred with prospective relevance for later use; while they need to be reformatted to active representations to guide behavior when needed (Stokes, 2015; Stokes et al., 2020). During the multi-state maintenance of working memory representations, the passive representations are mutually dissociated from the online

processing of active representations (Li et al., 2021; Oberauer, 2002).

According to the embedded processes models, it was traditionally thought that the passive representations were regarded as the product of transforming the active representations (Cowan, 1999; Oberauer, 2001, 2002). That is, when active representations were irrelevant to the current task and then offloaded to the passive state for later use, the passive representations were formed, which consequently freed active resources for the current processing of other active representations. It thus could be reasonably posited that a transition process conduced to the pattern of passive representations via transforming the active representations into the passive ones. However, that interpretation of passive representations appeared to contradict the alternative account. According to the dynamic coding for working memory-dependent behavior, the stimuli input triggered a specific memory pattern in the active state that in turn altered the underlying passive state of the network via short-term synaptic plasticity (Mongillo et al., 2008; Stokes, 2015). The passive state was modulated by the activity state via the reciprocal interaction between them. After the persistent activity relaxed to the baseline over the delay retention, the passive state still remained patterned according to the memory items; then the passive state would be never perturbed by irrelevant processing (Stokes, 2015). That seemed to imply that the passive representations had been formed as soon as the memory stimuli were encoded into working memory, coexisting with the memory pattern of active state. Thus, it could be plausibly reasoned that “offloading” the memory representations into the passive state might actually denoted the fade away of activity state, not

involving a transition of active representations.

Due to that the passive representations could not be detected by typical recording techniques, it was difficult to directly explore when the passive representations formed. Nevertheless, the two hypotheses mentioned above could be distinguished by verifying whether there was a transition process of active representations that brought about the pattern of passive representations.

Prior research provided us an effective experimental paradigm to unveil the question. In Zhang et al.'s study, the results showed that the first array was successfully transferred to the passive state in Experiment 3, which was manifested by the gradual dropout of CDA component from the first to the second delay (Zhang et al., 2021). However, their results pattern was inconsistent with the resource-dissociation account by showing an active setsize effect on the passive representations (Li et al., 2021). The incompatibility could be interpreted by the transition process account that the transition overlapped with subsequent consolidation of new stimuli in a such tight presentation period, resulting in resource competition, which was reflected by the active setsize effect on passive representations. Whereas the no-transition process account presented a diverse interpretation on the incompatibility. In that research, the passive representations were possibly not "hidden" due to that the activity state of these representations did not fully fade away when new stimuli were presented. Consequently, the activity state was interfered by subsequent stimuli, reflected by the active setsize effect on passive representations.

Here we attempted to adjudicate between the two hypotheses. Basing on the experimental paradigm and parameters of Zhang et al.'s experiments, we manipulated the presentation time of memory array 2 and the delay interval of two memory arrays in sequential presentation tasks. If a transition process was involved, we expected that the active setsize effect on passive representations was eliminated when extending the presentation time of memory array 2 sufficiently, in that the transition could complete prior to the subsequent active processing. In contrast, the passive representations were always affected by new perceptual representations irrespective of the presentation time if involving no transition process. The results of Experiment 1 conformed to the transition process account. Experiment 2 further suggested that the transition process always overlapped with subsequent active processing when the temporal context was beyond participants' anticipation, because the uncertainty of temporal context placed urgent demands of consolidating sensory stimuli into the active state. Experiment 3 indicated that the transition process could smoothly complete prior to the presentation of new stimuli if extending the delay interval sufficiently, thus never causing resource competition. Overall, these results demonstrated that a transition process was involved for the formation of passive representations. Therefore, we concluded that the passive representations were the product of transforming the active representations, rather than originated from the perceptual representations.

2 Experiment 1

The aim of Experiment 1 was to explore whether a transition process was involved for the formation of passive representations. Based on Zhang et al's

experiment, the delay interval was fixed at 800 ms, where the activity state of memory representations still remained when the memory array 2 appeared. If the active setsize effect on the passive representations observed in Zhang et al.'s research was caused by the overlap between transition and subsequent consolidation, we predicted that relatively long presentation time could eliminate the effect. Otherwise, that active setsize effect would be always observed regardless of the presentation time, which favored the no-transition process account.

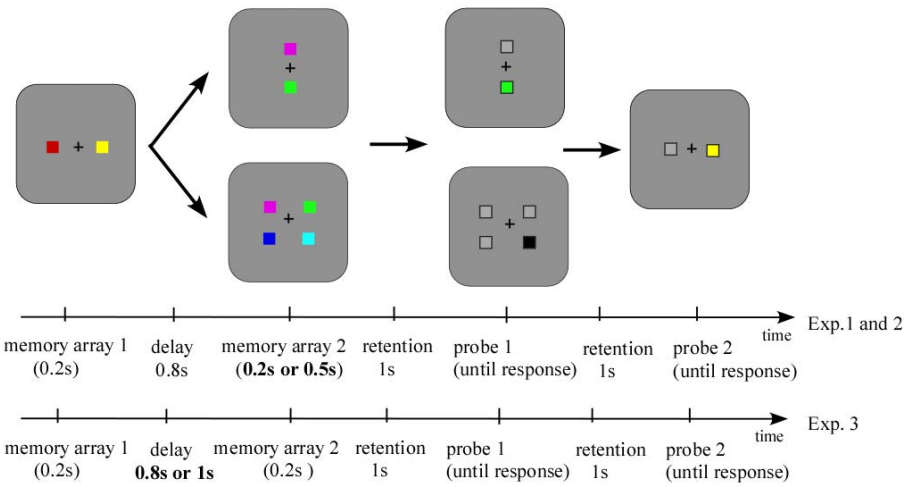

Figure 1: The schematic diagram of experimental tasks. Participants were instructed to remember all the colored squares in the two memory arrays. There are consistently two items in memory array 1. Memory array 2 presents two items in the low-load condition, and four items in the high-load condition. The items in memory array 2 are detected by probe 1. After responding to probe 1 and a short delay, the items in memory array 1 are detected by probe 2. The values below the boxes indicate the time interval.

2.1 Method

2.1.1 Participants

Sample-size determination was based on previous study that indicate the magnitude of the effect could be expected (Li et al., 2021). We used a similar sample size (30 in each experiment) to ensure the findings were reliable. None of the participants overlapped across experiments. 30 normal college students (six males; mean age: 22.07 ± 2.22 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.

2.1.2 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 by E-Prime 2.0 software. Responses were made using 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 screen and 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 memory stimuli were not perceptually overwritten. Participants adjusted their seat so that their eyes were level with the center of the screen before the beginning of trials. They were seated at a viewing distance of 70 cm in a chamber.

2.1.3 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 was modulated in a blocked design. Memory array 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 black border in each probe array was colored. These squares in probe 1 and probe 2 were congruent with memory items of memory array 2 and 1 correspondingly in number and spatial locations. During the detection phase, participants were instructed to decide whether the color of 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 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 complete the short and long presentation conditions with five blocks each, consisting of 320 trials in total. The order of the presentation condition was counterbalanced between subjects. The low- and high-load was randomly presented in each block. We ensured that the participants understood the procedure clearly by providing appropriate instruction and a practice session of 8 trials for each the short and long condition. 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 aim 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).

2.2 Data analysis

Data were analyzed by JASP software across the three experiments (Love et al., 2019). Effect size of the analyses of ANOVA are reported as $\eta^2 p$. For t-test concerning 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).

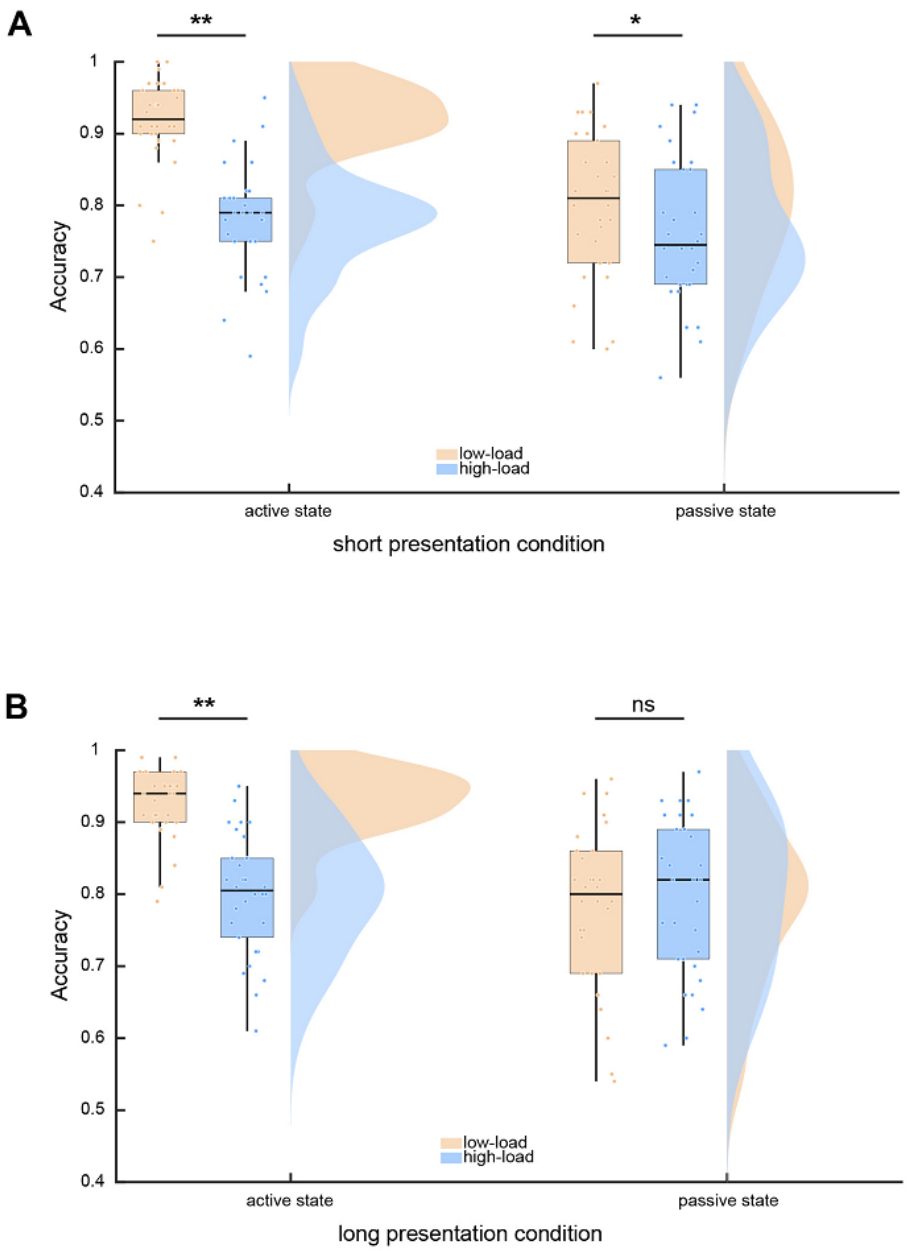

Figure 2: Mean accuracy in the active and passive states in the short (A) and long presentation conditions (B) in Experiment 1. The boxplot indicates the maximum, minimum, upper and lower quartiles, and median; the scatters indicate data distribution for each condition. The width of plot indicates density.

2.3 Results

The accuracy data were the main dependent measure. Probe 1 indicated

memory performance in the active state, while probe 2 indicated the passive state. 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 condition 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 is then analyzed and depicted in Figure 2.

For the short presentation condition (Figure 2A), accuracy data were analyzed separately by 2 (low-load vs. high-load) × 2 (active state vs. passive state) 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 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 of passive representations was also significantly higher in the low-load condition than in the high-load condition, t(29) = 3.658, p = 0.001, Cohen's d = 0.668, BF_{10} = 32.991. These results showed the active setseize effect on the passive representations in the such short presentation condition, which replicated Zhang et al.'s results pattern.

For the long presentation condition (Figure 2B), 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, $p < 0.001$, $\eta^2 p = 0.682$). This was driven by a lack of setsize effect on the passive representations. A 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 condition and the high-load condition, $t(29) = 1.121$, $p = 0.272$, Cohen's $d = 0.205$, $BF_{10} = 0.344$. These results showed that the active setsize effect on the passive representations was eliminated in the long presentation condition. That results pattern complied with the transition process account that the sufficient presentation time allowed for the transition process prior to subsequent active processing; thus, avoiding the overlap and resource competition.

2.4 Discussion

The results presented here suggested that the active setsize effect on the passive representations was eliminated in a relatively long presentation time. That followed that the interference with passive representations resulted from the overlap between transition and subsequent consolidation. Hence, we confirmed that the pattern of passive representations derived from the transformation of active representations via a transition process which required exclusive time and resources. Given that the temporal context was within participants' anticipation due to the blocked design, participants adopted appropriate strategies corresponding to the short and long presentation conditions. Nevertheless, it should be expected that, when the temporal

context was unpredictable, the transition process always overlapped with subsequent consolidation irrespective of the length of presentation time, because the uncertainty would place urgent demands of consolidating new stimuli into the active state. This hypothesis was tested in Experiment 2.

3 Experiment 2

The goal of Experiment 2 was to further verify the transition process for the formation of passive representations. In this part, the short and long presentation conditions were randomly presented within each block. We predicted that the time uncertainty led to an overlap and resources competition independently of the presentation time; thereby the active setsize effect on passive representations was observed even in the long presentation condition.

3.1 Method

3.1.1 Participants

Another 30 neurologically normal college students (5 males, mean age: 21.13 ± 2.39 years) were recruited in 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.

3.1.2 Stimuli and procedure

The schematic and procedure employed in Experiment 2 were identical to Experiment 1 excepting for the following (see Figure 1). The presentation time (200 ms vs. 500 ms) of memory array 2 were independent of the experimental block. The variable of presentation time and load was mixed within each block. The participants

were instructed to perform six blocks, consisting of 192 trials in total.

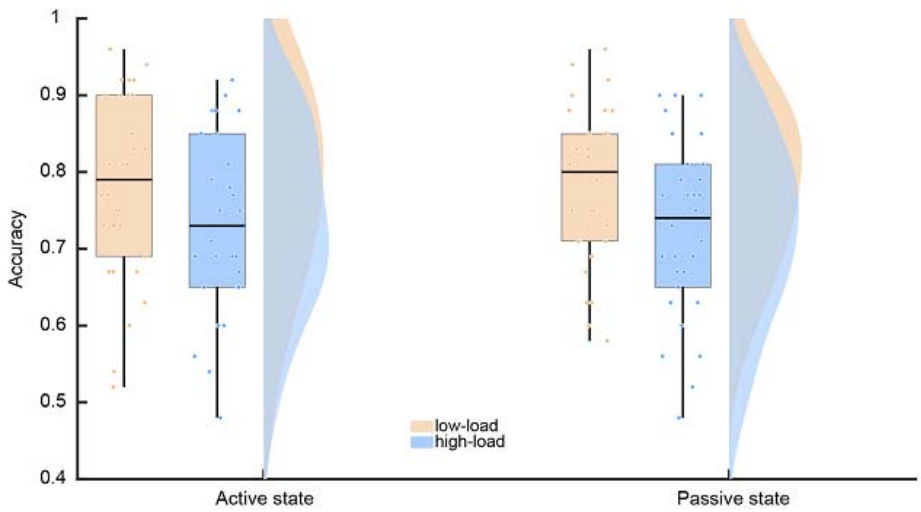

Figure 3: Mean accuracy of passive representations in Experiment 2. The boxplot indicates the maximum, minimum, upper and lower quartiles, and median; the scatters indicate data distribution for each condition. The width of plot indicates density.

3.2 Result

The passive memory accuracy was indicated by Probe 2. We conducted an ANOVA using the variables of load (low-load vs. high-load) and presentation time (200ms vs. 500 ms) for the accuracy data of passive representations. As depicted in Figure 3, 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 setsize effect on the passive representations was observed in both the short and long presentation conditions in the mixed design. In other words, the transition process always overlapped with subsequent consolidation because of the unpredictability of the

temporal context.

3.3 Discussion

As expected, the unpredictability of the temporal context resulted in the overlap of transition and subsequent consolidation independent of the temporal context, because the unpredictability drove participants to urgently initiate subsequent consolidation in case the new stimuli visually disappeared. Together with results of Experiment 1, it demonstrated that the overlap between the transition process and subsequent consolidation resulted from psychologically insufficient temporal context. These findings further revealed that the formation of passive representation involved a transition process which required exclusive time and resources.

4 Experiment 3

It has suggested that the transition process required exclusive time and resources in previous two experiments. In light of these findings, we reckoned that the transition process could smoothly complete prior to the presentation of new stimuli if extending the delay interval sufficiently, so that never encountering the subsequent active processing. Thus, we predicted that there was no active setsize effect on the passive representations in a relatively long delay condition.

4.1 Method

4.1.1 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.

4.1.2 Stimuli and procedure

All materials and 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 for 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 condition was assessed in a blocked 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 delay condition was counterbalanced between subjects. The low- and high-load was randomly presented in each block with equal probability.

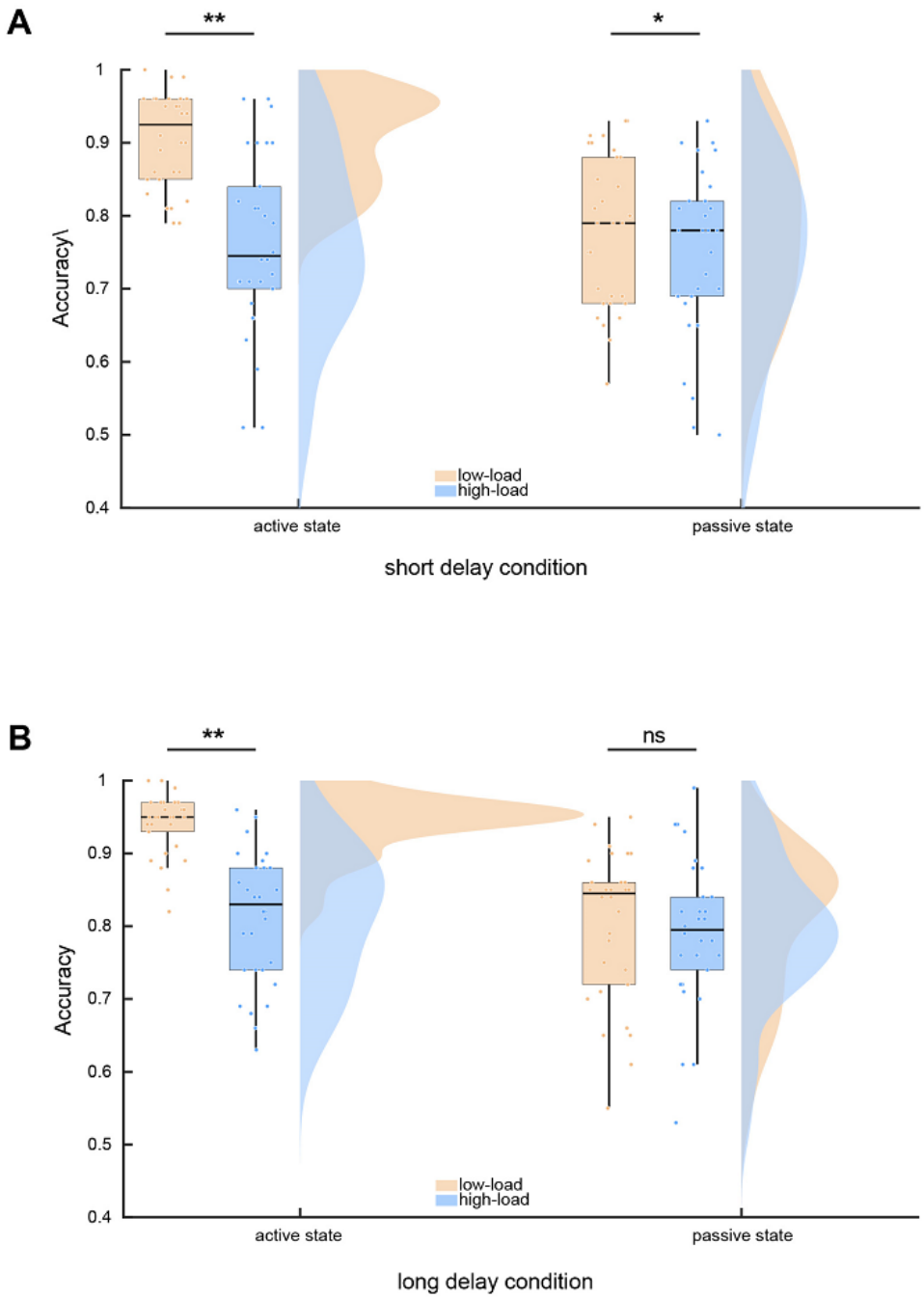

Figure 4: Mean accuracy in the active and passive states in short (A) and long (B) delay conditions in Experiment 3. The boxplot indicates the maximum, minimum, upper and lower quartiles, and median; the scatters indicate data distribution for each condition. The width of plot indicates density.

4.2 Results

The data across all participants were subject to the same analysis plan as Experiment 1 (Figure 4). 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, $p < 0.001$, $\eta^2 p = 0.609$). 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, $p < 0.001$, $\eta^2 p = 0.377$), 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 short delay caused an effect of active setsize effect on the passive representations, which replicated the results of Experiment 1.

An important analysis on 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 a null active setsize effect on the 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 between 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 suggested that the passive representations were not affected by active setsize effect when extending the delay interval, which was attributed to a smooth transition to the passive state before the presentation of subsequent stimuli.

4.3 Discussion

As we expected, the passive representations were not interfered by the active setsize variation when extending the delay retention sufficiently. That results pattern indicated that, when the delay interval was sufficiently long, the transition process could smoothly complete prior to the presentation of subsequent stimuli. So that the transition never overlapped with subsequent cognitive processing, thus averting resource competition. Together, we concluded that the passive representations could be robustly patterned without being triggered by new stimuli, which, notably, benefited from a smooth transition process in a sufficient temporal context.

5 General discussion

The primary aim of the current study was to investigate how the passive representations were patterned, which was indirectly assessed by the exploration whether a transition process was involved when the maintenance pattern was changed into the passive state. The passive representations should be independent of the active load variation according to the resource-dissociation account(Li et al., 2021), however, the active setsize effect on the passive representations was detected in some scenarios. The current results attributed the odd effect to the resource competition that resulted

from the overlap between transition and subsequent consolidation in a physically or psychologically insufficient temporal context. That thus suggested an involvement of transition process for the formation of passive representations across three experiments. Also, it has shown that the transition process could smoothly complete prior to the presentation of new stimuli if the delay interval was sufficient enough. That revealed that the recruitment of passive maintenance was not necessarily triggered by new stimuli, but the secondary task demands. Together, these results evidenced the proposal that the passive representations were the product of transformation of active representations, denying the assumption that the perceptual representations directly entered into the passive state for temporary maintenance.

The current results in fact fall in with resource-dissociation account of VWM (Li et al., 2021; Oberauer, 2002). Notably, the temporal context played a critical role in a smooth transition of active representations into the passive. It has previously proposed that event processing that crowed in a psychological timeline tended to result in interference with each other (Souza & Oberauer, 2014). Thus, a sufficient time period allowed for a smooth transition prior to subsequent active processing, which contributed to a perfect independence of passive representations from the active processing. In terms of the resource competition in the relatively tight temporal context, we reasoned that the cognitive resources for the state transition was conceivably not domain-specific, but shared with sensory consolidation of new stimuli into the active state (LaRocque et al., 2013). In addition, the current results inspired us to conclude that a perfect dissociation of the active and passive states

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 time period reserved for the transition process per se during either the delay interval or the presentation of subsequent stimuli.

The activity-silent model of VWM depicted a dynamic coding framework for working memory from the neuropsychological perspective. With regard to the pattern of passive representations, this model presumed that the passive pattern of memory representations coexisted with their activity pattern as the memory stimuli were consolidated into VWM (Stokes, 2015). This notion, however, was incompatible with the current findings that the passive representations were the product of the transformation of active representations. The current study suggested a slight modification of the activity-silent model in terms of how the activity-silent state was patterned. Considering that the synaptic connectivity underpinned long-term memory, we plausibly assumed that temporary retention in the passive state could benefit their long-term memory trace (McCabe, 2008; Rose et al., 2014), because the passive representations promoted the weight-based changes of synaptic connectivity. From this perspective, these findings seemed to offer a way to optimize the long-term memory maintenance in mind.

The current research bears strong relevance to current effort to dynamic processing of VWM (de Vries et al., 2020; Masse et al., 2020; Rose, 2020). Different from the recurrent neural activity, the synaptic changes in connectivity are far more

energy efficient since they do not have to be continuously upheld like recurrent activity patterns. Thus, the representational transition into the passive state might manifest great evolutionary advantage on some degree (Chota & van der Stigchel, 2021; Stokes, 2015). In the current study, the number of passive representations was fixed at two. That leaves up the question whether more time was secured for a smooth transition. What's more, these findings about how the passive representations were patterned are indirectly obtained from behavioral results through three experiments; thus, the neural mechanisms underlying the state transition is necessarily explored with electrophysiological and neuroimaging techniques. Further research needed to be conducted to advance the understanding of multistate maintenance of VWM.

6 Conclusion

In summary, the current results suggested that a transition process was involved for the formation of passive representations. That evidenced the proposal that the pattern of passive representations derived from the transformation of active representations, rather than the perceptual representation of memory stimuli. The current results implied that, at the neural level, the passive pattern of memory representations did not accompany with its activity state. Moreover, these findings provide practical implication that the temporary retention in the passive state could boost memory trace in long-term memory, given that the passive pattern contributing to the changes of synaptic connectivity.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (NSFC31970989).

Declarations of interest: none.

Reference

Aben, B., Stapert, S., & Blokland, A. (2012). About the Distinction between Working Memory and Short-Term Memory. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00301

Baddeley, A. (1992). Working memory. *Science*, *255*(5044), 556–559. https://doi.org/10.1126/science.1736359

Baddeley, Alan., & Hitch, G. (1974). Working memory. Psychology of Learning and Motivation - Advances in Research and Theory. https://doi.org/10.1016/S0079-7421(08)60452-1

Chota, S., & van der Stigchel, S. (2021). Dynamic and flexible transformation and reallocation of visual working memory representations. Visual Cognition, 29(7), 409–415. https://doi.org/10.1080/13506285.2021.1891168

Cowan, N. (1999). An embedded-processes model of working memory. Models of working memory. In Models of Working Memory: Mechanisms of Active Maintenance and Executive Control.

de Vries, I. E. J., Slagter, H. A., & Olivers, C. N. L. (2020). Oscillatory Control over Representational States in Working Memory. Trends in Cognitive Sciences, 24(2), 150–162. https://doi.org/10.1016/j.tics.2019.11.006

Johanna Kreither, Papaioannou, O., & Luck, S. J. (2022). Active Working Memory and Simple Cognitive Operations. Journal of Cognitive Neuroscience, 34(2), 313–331.

LaRocque, J. J., Eichenbaum, A. S., Starrett, M. J., Rose, N. S., Emrich, S. M., & Postle, B. R. (2015). The short- and long-term fates of memory items retained outside the focus of attention. Memory & Cognition, 43(3), 453–468. https://doi.org/10.3758/s13421-014-0486-y

LaRocque, J. J., Lewis-Peacock, J. A., Drysdale, A. T., Oberauer, K., & Postle, B. R. (2013). Decoding Attended Information in Short-term Memory: An EEG Study. *Journal of Cognitive Neuroscience*, *25*(1), 127–142. https://doi.org/10.1162/jocn_a_00305

Lewis-Peacock, J. A., Drysdale, A. T., Oberauer, K., & Postle, B. R. (2012). Neural evidence for a distinction between short-term memory and the focus of attention. Journal of Cognitive Neuroscience. https://doi.org/10.1162/jocn_a_00140

Li, Z., Liang, T., & Liu, Q. (2021). The storage resources of the active and passive states are independent in visual working memory. Cognition, 217(June 2020), 104911. https://doi.org/10.1016/j.cognition.2021.104911

Li, Z., Zhang, J., Liang, T., Ye, C., & Liu, Q. (2020). Interval between two sequential arrays determines their storage state in visual working memory. Scientific Reports, 10(1), 1–9. https://doi.org/10.1038/s41598-020-64825-4

Love, J., Selker, R., Marsman, M., Jamil, T., Dropmann, D., Verhagen, J., Ly, A., Gronau, Q. F., Šmíra, M., Epskamp, S., Matzke, D., Wild, A., Knight, P., Rouder, J. N., Morey, R. D., & Wagenmakers, E. J. (2019). JASP: Graphical statistical software for common statistical designs. Journal of Statistical Software, 88(1). https://doi.org/10.18637/jss.v088.i02

Masse, N. Y., Rosen, M. C., & Freedman, D. J. (2020). Reevaluating the Role of Persistent Neural Activity in Short-Term Memory. Trends in Cognitive Sciences, 24(3), 242–258. https://doi.org/10.1016/j.tics.2019.12.014

McCabe, D. P. (2008). The role of covert retrieval in working memory span tasks: Evidence from delayed recall tests. Journal of Memory and Language, 58(2), 480–494. https://doi.org/10.1016/j.jml.2007.04.004

Mongillo, G., Barak, O., & Tsodyks, M. (2008a). SynaptiC Theory of Working Memory. Science, 319(5869), 1543–1546. https://doi.org/10.1126/science.1150769

Mongillo, G., Barak, O., & Tsodyks, M. (2008b). Synaptic Theory of Working Memory. Science, 319(5869), 1543–1546. https://doi.org/10.1126/science.1150769

Muhle-Karbe, P. S., Myers, N. E., & Stokes, M. G. (2021). A hierarchy of functional states in working memory. Journal of Neuroscience, 41(20), 4461–4475. https://doi.org/10.1523/JNEUROSCI.3104-20.2021

Nee, D. E., & Jonides, J. (2013). Trisecting representational states in short-term memory. Frontiers in Human Neuroscience, 7. https://doi.org/10.3389/fnhum.2013.00796

Oberauer, K. (2001). Removing Irrelevant Information from Working Memory: A Cognitive Aging Study with the Modified Sternberg Task. Journal of Experimental Psychology. Learning, Memory, and Cognition, 27, 948–957. https://doi.org/10.1037/0278-7393.27.4.948

Oberauer, K. (2002). Access to Information in Working Memory: Exploring the Focus of Attention. Journal of Experimental Psychology: Learning Memory and Cognition, 28(3), 411–421. https://doi.org/10.1037/0278-7393.28.3.411

Oberauer, K. (2005). Control of the contents of working memory - A comparison of two paradigms and two age groups. Journal of Experimental Psychology: Learning Memory and Cognition, 31(4), 714–728. https://doi.org/10.1037/0278-7393.31.4.714

Oberauer, K., & Awh, E. (2022). Is There an Activity-silent Working Memory? Journal of Cognitive Neuroscience, 1–15. https://doi.org/10.1162/jocn_a_01917

Rose, N. S. (2020). The Dynamic-Processing Model of Working Memory. Current Directions in Psychological Science, 29(4), 378–387. https://doi.org/10.1177/0963721420922185

Rose, N. S., Buchsbaum, B. R., & Craik, F. I. M. (2014). Short-term retention of a single word relies on retrieval from long-term memory when both rehearsal and refreshing are disrupted. Memory and Cognition, 42(5), 689–700. https://doi.org/10.3758/s13421-014-0398-x

Rose, N. S., Joshua J. LaRocque, Adam C. Riggall, O. G., & Michael J. Starrett, Emma E. Meyering, B. R. P. (2016). Reactivation of latent working memories with transcranial magnetic stimulation. Science, 354(6316), 1136–1139. https://doi.org/10.1126/science.aah7011.Reactivation

Schmalz, X., Manresa, J. B., & Zhang, L. (2021). What Is a Bayes Factor? Psychological Methods, November. https://doi.org/10.1037/met0000421

Shaffer, W., & Shiffrin, R. M. (1972). Rehearsal and storage of visual information. Journal of Experimental Psychology. https://doi.org/10.1037/h0032076

Souza, A. S., & Oberauer, K. (2014). Time-based forgetting in visual working memory reflects temporal distinctiveness, not decay. Psychonomic Bulletin and Review, 22(1), 156–162. https://doi.org/10.3758/s13423-014-0652-z

Stokes, M. G. (2015). “Activity-silent” working memory in prefrontal cortex: A dynamic coding framework. Trends in Cognitive Sciences, 19(7), 394–405. https://doi.org/10.1016/j.tics.2015.05.004

Stokes, M. G., Muhle-Karbe, P. S., & Myers, N. E. (2020). Theoretical distinction between functional states in working memory and their corresponding neural states. Visual Cognition, 28(5–8), 420–432. https://doi.org/10.1080/13506285.2020.1825141

Todd, J. J., & Marois, R. (2004). Capacity limit of visual short-term memory in human posterior parietal cortex. Nature, 428(6984), 751–754. https://doi.org/10.1038/nature02466

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. Nature, 428(6984), 748–751. https://doi.org/10.1038/nature02447

Wolff, M. J., Ding, J., Myers, N. E., & Stokes, M. G. (2015). Revealing hidden states in visual working memory using electroencephalography. Frontiers in Systems Neuroscience, 9(september), 1–12. https://doi.org/10.3389/fnsys.2015.00123

Wolff, M. J., Jochim, J., Akyürek, E. G., & Stokes, M. G. (2017). Dynamic hidden states underlying working memory guided behaviour. Nature Neuroscience, 20(6), 864–871. https://doi.org/10.1038/nn.4546.Dynamic

Zhang, J., Ye, C., Sun, H.-J., Zhou, J., Liang, T., Li, Y., & Liu, Q. (2021). The passive state: A protective mechanism for information in working memory tasks. Journal of Experimental Psychology: Learning, Memory, and Cognition.

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. Nature, 453(7192), 233–235. https://doi.org/10.1038/nature06860.