The passive representations are the product of transformation of active representations in visual 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 formed. 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 representational state, 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 of active representations. 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) plays a foundational role in advanced cognitive functions. It serves to retain and manipulate the information in mind (Baddeley, 1992; Eriksson et al., 2015; Miller et al., 2018). Previous study has focused on the exploration of working memory maintenance with a single state, which was conceptually equivalent to the active state (Adam1 et al., 2018; Feldmann-Wüstefeld et al., 2018; 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 sustained neural activity (LaRocque et al., 2013; Lewis-Peacock et al., 2012; Johanna Kreither et al., 2022), the passive representations are effectively maintained via the weight-based changes of synaptic plasticity, thus no detection of sustained activity (Eriksson et al., 2015; Mongillo et al., 2008; 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 frame of working memory, the input stimuli triggered a specific active memory pattern that in turn altered the passive state of the network via the changes of functional connectivity (Mongillo et al., 2008; Stokes, 2015). That is, 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. Hence, it seemingly posed an assumption 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 presenting memory array 2 with a relatively long time, because 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, in that 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

This experiment 1 sought 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 0.8 s, 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.

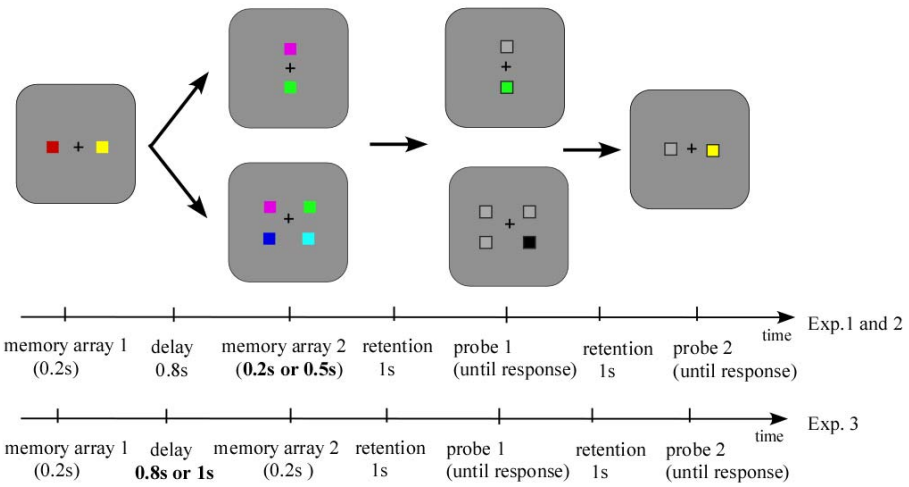

Figure 1: The schematic diagram of the experimental events. The colored squares are designed as memory items. Memory array 1 always presented two items; memory array 2 presented two or four items randomly within a trial. Memory array 1 and memory array 2 were detected by probe 2 and probe 1, respectively. The time frame of memory events is indicated by the numbers below.

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. We recruited 30 participants in Experiment 1 (M = 22.07 years, SD = 2.22; 6 male). Their vision and color vision were normal or corrected-to-normal. Participants all signed the informed consent before the experiment start, and received 30 CNY after the completion. All experiments complied with the Declaration of Helsinki. The present research has gained permission from the Human Research Institutional Review Board in Liaoning Normal University.

2.1.2 Apparatus and stimuli

We employed E-Prime 2.0 to run the experiment procedures in a 19-inch LCD monitor (60-Hz refresh rate, 1920 × 1080 pixels). A fixation cross (0.23°) was shown centrally in the screen, never disappeared through the whole trials. Colored squares (0.49° × 0.49°) were selected as memory stimuli. The color of memory squares was selected from a color pool (blue, black, red, magenta, lime, purple, yellow, and cyan) without repetition within a trial. The squares in memory array 1 were located horizontally at the level of fixation cross in the left and right sides. In memory array 2, the squares were located along the midline when two items were presented, while they were located in the left and right sides separately with two in each side when remembering four items. The locations of all memory items were consistently on a invisible square (1.80° × 1.80°) around the fixation. In the two probe arrays, the locations previously presenting memory items were occupied by square outlines, one

of which was colored. The locations of items in probe 1 corresponded with the memory array 2, and probe 2 corresponded with memory array 1. The distance between participants and screen fixed at 70 cm. The height of fixation cross leveled with participants' eyes.

2.1.3 Procedure

As depicted in Figure 1, the first array was presented for 0.2 s for encoding two items, which was followed by a delay interval of 0.8 s. Then the second array appeared for either 0.2 s or 0.5 s in a blocked design; meanwhile, two or four items were randomly presented in each trial with an equal probability. After the second delay, two probe arrays sequentially appeared to detect the memory of memory array 1 and then memory array 2 in a reverse order manner. The two probe arrays were separated by an interval of 1 s. The accuracy was stressed over speed. The presentation of probe arrays thus had no time limit, which disappeared once making response. If the colored items in the probe arrays were the same as the memory items in the corresponding locations, participants made "same" response by pressing "Z" in the keyboard, or making "different" response by pressing "M". The same and different responses for each probe were fully random with 50% probability in each block. In the different trials, the color of probe items was selected from eight possible colors mentioned above, but never used by previous memory items in one trial.

Participants need to perform the short and long presentation blocks with five blocks each, creating a total of 320 trials. A half of participants performed the short presentation blocks first and the long presentation blocks later, while the other half

performed the long presentation blocks first and the short presentation blocks later. Before the formal trials, we provided an instruction and a practice session of 8 trials to ensure that each participant was familiar with the procedure. To prevent the contamination of verbal encoding, participants were asked to perform the subvocal rehearsal of digits when performing the memory tasks (Shaffer & Shiffrin, 1972).

2.2 Data analysis

Data were analyzed by JASP software across the three experiments (Love et al., 2019). We reported $\eta^2 p$ to index the effect size. For t-test concerning the setsize effect on active and passive memory, Cohen's d was calculated to show effect size. Bayes factors were included to quantify the evidence for the alternative over the null hypothesis (Schmalz et al., 2021).

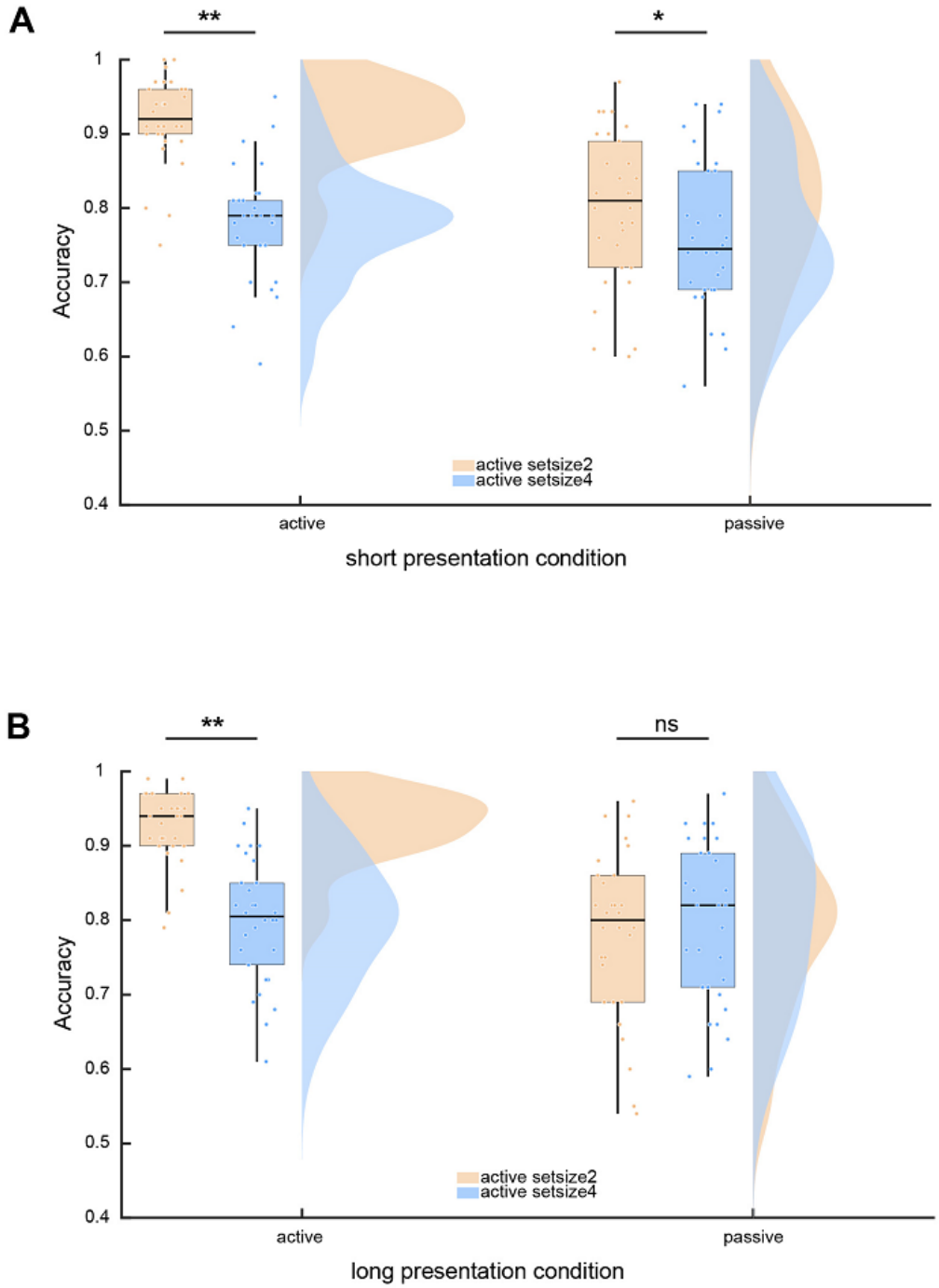

Figure 2: Behavioral accuracy of active and passive representations in the short (A) and long (B) presentation conditions in Experiment 1. Boxplot, the middle lines indicate the median; the box outlines represent the 1st and 3rd quartiles. Scatters indicate data distribution for each condition.

2.3 Results

Probes 1 and 2 indicated the memory accuracy of active representations and passive representations, respectively. This experiment was designed in a within-subject manner, including three variables, active setsize, representational state and presentation time. A 2 (active setsize 2 vs. active setsize 4) × 2 (active state vs. passive state) × 2 (0.2 s vs. 0.5 s) ANOVA was conducted, and the results showed a significant interaction of presentation time and active setsize, F (1, 29) =8.229, p = 0.008, $\eta^2 p$ = 0.221. Then we analyzed the behavioral accuracy in the short and long presentation conditions separately, which allowed us to distinguish the active setsize effect on the passive representations in the two presentations.

For the short presentation condition (Figure 2A), the results of 2 (active setsize 2 vs. active setsize 4) × 2 (active state vs. passive state) ANOVA showed a significant interaction, F (1, 29) = 35.603, $p < 0.001$, $\eta^2 p$ = 0.551. That was caused by a larger accuracy decrease for the active memory relative to the passive memory. Subsequent simple effect analysis showed that the active memory accuracy had a significant decrease when the setsize increased from two to four, t(29) = 14.699, $p < 0.001$, Cohen's d = 2.684, BF_{10} = 1.115e+12. Also, the passive memory accuracy decreased when increasing the active setsetize, 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 presentation time of 0.2 s, which replicated Zhang et al.'s results pattern. For the long presentation condition (Figure 2B), a similar 2 × 2 ANOVA showed a significant interaction, 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 memory. A subsequent t-test on these

data suggested that the active accuracy consistently impaired due to the larger setsize, $t(29) = 8.846$, $p < 0.001$, Cohen's $d = 1.615$, $BF_{10} = 1.148e+7$. However, the passive memory accuracy of was comparable in the conditions of active setsize 2 and 4, $t(29) = 1.121$, $p = 0.272$, Cohen's $d = 0.205$, $BF_{10} = 0.344$. Together, it has shown that there was no active setsize effect on the passive representations when extending the presentation time of memory array 2. This 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. The

following experiment examined this hypothesis.

3 Experiment 2

This experiment sought 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

A sample of 30 (5 males) were recruited (mean age: 21.13 ± 2.39 years), without overlap with Experiment 1. All participants reported normal and corrected-to-normal vision, and normal color vision. They signed the informed consent forms when arriving the lab, and received 30 CNY for compensation.

3.1.2 Stimuli and procedure

Similar to the procedure and stimuli of preceding experiment (see Figure 1), this experiment nevertheless made a slight modification. The presentation time (0.2 s vs. 0.5 s) 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.

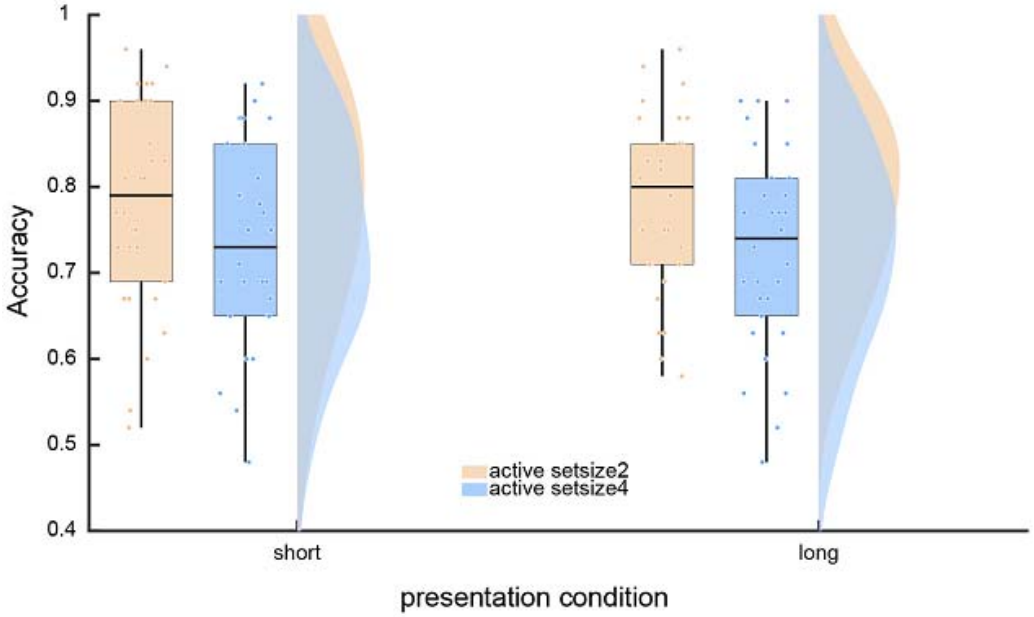

Figure 3: Mean accuracy of passive representations in Experiment 2. Boxplot, the middle lines indicate the median; the box outlines represent the 1st and 3rd quartiles. Scatters indicate data distribution for each condition.

3.2 Result

The memory accuracy of passive representations was indicated by Probe 2. We conducted an ANOVA using the variables of active setsize (active setsize 2 vs. active setsize 4) and presentation time (0.2 s vs. 0.5 s) for the accuracy data of passive representations. As depicted in Figure 3, the active setsize showed a significant main effect, F (1, 29) = 16.335, $p < 0.001$, $\eta^2 p = 0.360$. Importantly, the factor active setsize did not interact with presentation time (F < 1). Thus, it followed 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, in a relatively long delay condition, there was no active setsize effect on the passive representations.

4.1 Method

4.1.1 Participants

Another sample of 30 was recruited (5 males; mean age: 21.97 ± 2.70 years). Participants reported normal and corrected-to-normal vision, and normal color vision. they had provided informed consent forms before carrying out the experiment, and

they would receive 30 CNY for their participation after the completion.

4.1.2 Stimuli and procedure

This part repeated “stimuli and procedure” of Experiment 1 and made a slight modification (see Figure 1). Memory array 2 appeared for a fixed time of 0.2 s. While the delay interval between two memory arrays lasted 0.8 s or 1 s in a blocked design. The active setsize 2 and 4 were randomly presented in each trial with equal probability. We designed 5 blocks of each delay condition, creating 320 trials totally for each participant. The order of short and long delay blocks was balanced between participants.

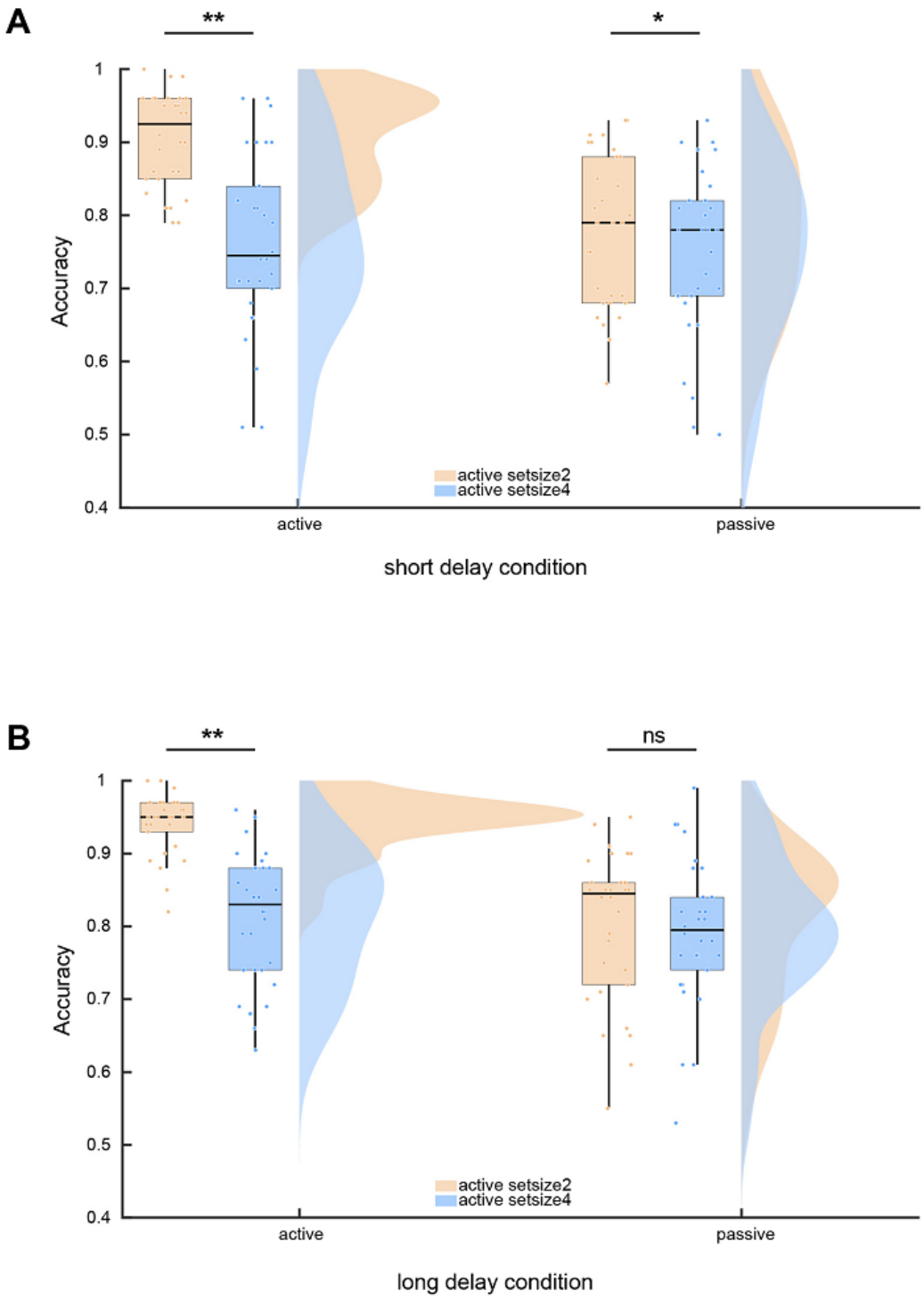

Figure 4: Mean accuracy of active representations and passive representations in short (A) and long (B) delay conditions in Experiment 3. Boxplot, the middle lines indicate the median; the box outlines represent the 1st and 3rd quartiles. Scatters

indicate data distribution for each condition.

4.2 Results

The collective data underwent the similar analysis plan to Experiment 1 (Figure 4). A 2 (active setsize 2 vs. active setsize 4) × 2 (active state vs. passive state) × 2 (0.8 s vs. 1 s) ANOVA revealed a statistically significant interaction between representational state and active setsize, F (1, 29) = 45.259, $p < 0.001$, $\eta^2 p = 0.609$. Then we run a 2 × 2 ANOVA with factors active setsize and representational state for the short and long delay conditions separately. In the short delay condition (Figure 4A), the results showed a statistically significant interaction, F (1, 29) = 17.522, $p < 0.001$, $\eta^2 p = 0.377$. That was driven by a smaller accuracy decrease of passive memory relative to the active memory when increasing the active setsize. Subsequent test analysis suggested that the active memory accuracy was much higher in the setsize 2 than the setsize 4, $t(29) = 6.749$, $p < 0.001$, Cohen's $d = 1.232$, $BF_{10} = 75595.299$. While the passive memory was also higher in the smaller active setsize condition, $t(29) = 3.044$, $p = 0.005$, Cohen's $d = 0.556$, $BF_{10} = 8.249$.

The analysis on the long delay condition was of us interest (Figure 4B). The 2 × 2 ANOVA results showed that the representational state significantly interacted with active setsize, F (1, 29) = 36.239, $p < 0.001$, $\eta^2 p = 0.555$, which was driven a null effect of active setsize on the passive memory. The subsequent test analysis showed that the active memory suffered a decrease when the active setsize increased from two to four, $t(29) = 8.682$, $p < 0.001$, Cohen's $d = 1.585$, BF_{10}= 7.879e+6. Whereas the passive memory was kept constant in the conditions of active setsize 2 and 4, $t(29) = 0.813$, $p = 0.423$, Cohen's $d = 0.148$, $BF_{10} = 0.263$. Overall, we concluded 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 present study primarily aimed to explore how the passive representations were patterned. That inspired us to assess 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 accompanied by sustained firing. 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.

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Declarations of interest: none.

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