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

Ziyuan Li[a,b], Qiang Liu [a,b*]

a. Institute of Brain and Psychological Sciences, Sichuan Normal University, Chengdu, China, 610000

b. Research Center of Brain and Cognitive Neuroscience, Liaoning Normal University, Dalian, China, 116029

Abstract

The passive state serves robust maintenance for the memory representations, which performed a functionally different role from the active state during the mlutistate maintenance in visual working memory. However, it is still unclear how the passive representations are formed. The current study was based on the embedded process model and activity-silent model to explore this question by adopting a sequential presentation paradigm. The temporal modulation focused on the presentation time of subsequent stimuli and the retention interval between the two memory arrays. These results demonstrated that the passive representation was consciously formed via the representational transition from the active state, rather than in a spontaneous manner during memory encoding period; moreover, the representational transition was driven by cognitive demands. The current study presented the insights on the contribution of the 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 the 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 as comprising 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 the ongoing processing; the memory maintenance in the active state is assumed to critically depend on persistent neural activity (Kamiński & Rutishauser, 2020; Manohar et al., 2019; Stokes, 2015). Notably, the memory can be well maintained in the passive state over a short delay with the absence of sustained neural activity that tracked that memory (LaRocque et al., 2013; Lewis-Peacock et al., 2012a; Stokes, 2015). Proponent of the passive maintenance argued that the memory representations were effectively maintained through weight-based changes in synaptic connectivity (Mongillo et al., 2008; Muhle-Karbe et al., 2021; Stokes, 2015). In contrast to the active representations, the passive representations are temporarily irrelevant to the ongoing processing and exert little influence on it. Accumulating evidence has demonstrated that the passive representations are robust and resistant to the interference and time decay (Johanna

Kreither, 2021; Stokes et al., 2020; Zhang et al., 2021). Importantly, the passive representations need to be reformatted into active ones that allow them to guide behaviour when needed (Stokes, 2015; Stokes et al., 2020). The view that memory representations were dynamic and modifiable via cognitive control has been supported by the observation of a reactivation effect of passive representations following 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 the resources in the active and passive states were independent of each other (Li et al., 2021; Oberauer, 2002).

The state-based theory of working memory has been supported by the embedded process models and the activity-silent models, which elucidated the representational state from the perspective of the functional roles and neurophysiological mechanisms, respectively. The two theoretical models presented different views on the source of passive representations. The embedded process model proposed that memory representation existed in one of the two states. When attention subsequently shifted to other information, the memory representation that was previously in the active state dropped its active format and transitioned to the passive state (LaRocque et al., 2014). Hence, the passive representations were assumed to consciously form via representational transition from the active state according to the task demands. While the activity-silent model argued that the passive format of memory representation emerged accompanying with 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 existed following the attenuation of neural activity when attention shifted towards other items. Thus, the passive representation was supposed to spontaneously form once the sensory stimulus has been encoded into VWM. However, there is rare study to empirically explore how the passive representation forms during the multistate maintenance.

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

Prior research provided us 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 EEG recordings have indicated that the first set were retained in the passive state during the active processing of the second set. Their behavioral results pattern was incompatible with the resource-dissociation account by showing an effect of the active load variation on the passive

representations. The incompatibility presumably imply that the memory representations presented firstly had not dropped the active format yet when the subsequent stimuli appeared. The representational transition account presumed that such 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 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 the passive representations. Whereas, in light of the activity attenuation account, the memory representations without the drop of active format were presumed to be definitely interfered by subsequent stimuli, due to that the sensory processing on the new stimuli elicited the neural activation in primary visual cortex. Such that the passive format underlying the memory representations was correspondingly affected. 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 active format of the memory representations accompanied with representational transition or not, which could account for how the passive representations formed. We adopted a sequential presentation tasks modeled after Zhang et al.'s (2021). Firstly, the presentation of subsequent stimuli was modulated in Experiment 1, where the short and long presentation randomly appeared within each block. Unfortunately, the results failed to convincingly evidence either of 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, so that participants could well predict the temporal context in the following trial. The results denied the activity attenuation account and evidenced the representational transition to the passive state following the drop of active format. Then, the delay retention between two arrays was modulated in Experiment 3, and the results further evidenced the representational transition for the 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 presentation of subsequent stimuli to test our hypotheses; the short and long presentation time randomly appeared within each block. We predicted that, if there was 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 be not 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.

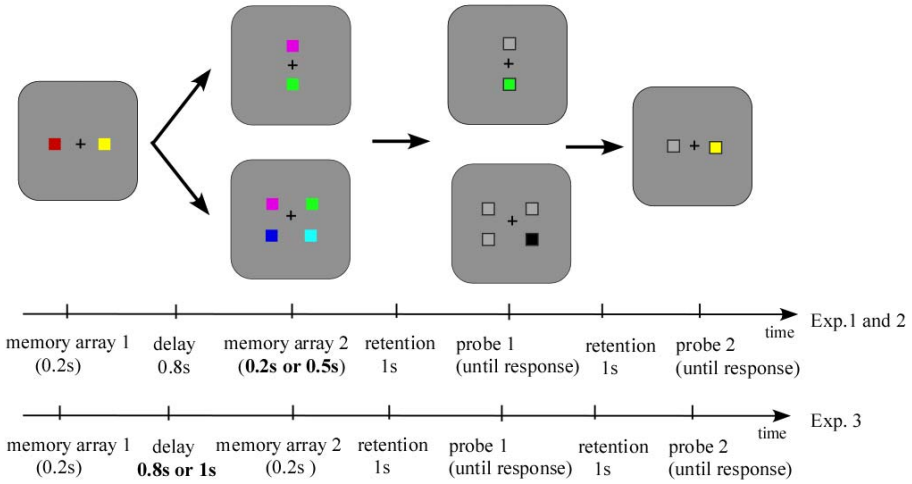


Figure 1: A schematic diagram of the task in Experiment 1, 2 and 3. Participants were instructed to remember all the colored squares in the two memory arrays. There are consistently two items in memory array 1. Memory array 2 presents two items in the low-load condition, and four items in the high-load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

Method

Participants

Sample-size determination was based on 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 the findings were reliable. None of the

participants overlapped across experiments. 30 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 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.

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 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 manner of encoding and detection encouraged participants to retain memory array 1 and 2 in the passive and active state, 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 6 blocks, consisting of 192 trials in total. The variable of presentation time and load was mixed within each block. We ensured that the participants understood the procedure clearly by providing appropriate instruction and a practice session of 8 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 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).

Data were analyzed by JASP software (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).

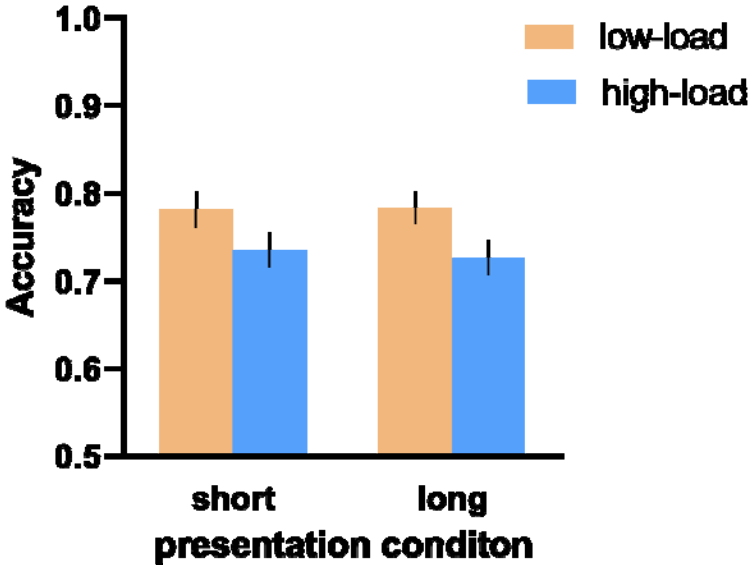


Figure 2: Mean accuracy in the passive state in Experiment 1. Error bars indicate the standard error.

Result

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 (200ms 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 had an effect on the passive representations in both the short and the long presentation conditions. On one hand, 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 the 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 the subsequent active processing. Then, 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 temporal context. Therefore, we attempted to rescue the temporal predictability to further explore whether the drop of active format conformed to the representational transition account or the activity attenuation account in the following experiment.

Experiment 2

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

Method

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 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 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 presentation condition was counterbalanced between subjects. The low- and high-load was 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 8 trials for each the short and long presentation condition.

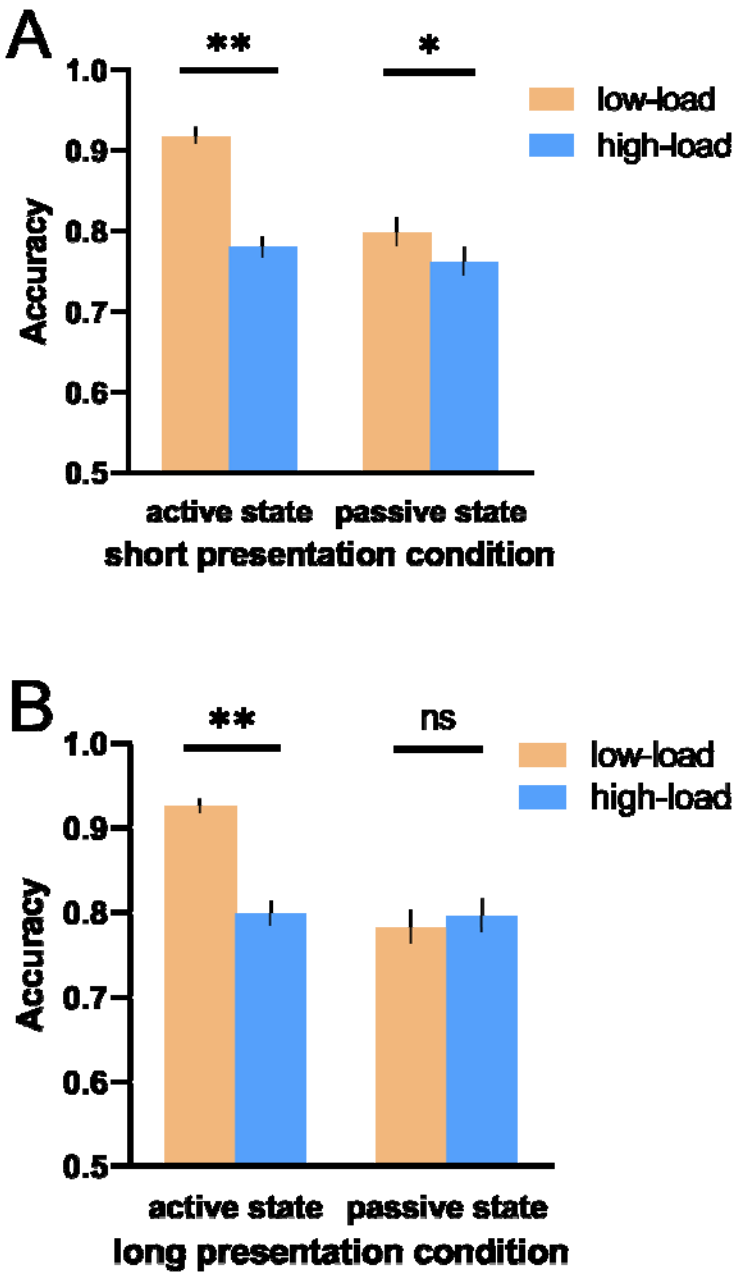


Figure 3: Mean accuracy in the active and passive states in the short presentation condition (A) and the long presentation condition (B) in Experiment 2. Error bars indicate the standard error.

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 is 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 the 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 the high-load conditions, $t(29) = 1.121$, $p = 0.272$, Cohen's $d = 0.205$, $BF_{10} = 0.344$. These results suggested that there was no effect of active load variation on the passive representations in the long presentation of subsequent stimuli, which showed a different results pattern from the short presentation condition.

Discussion

These results presented suggested that the sufficient presentation of subsequent stimuli removed the effect of active load variation on the 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 conduced to the representational transition to the passive state. In addition, the current findings also 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 the passive representation was consciously formed via the representational transition from the active state, which denied the spontaneity of passive representations. Basing 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 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 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.

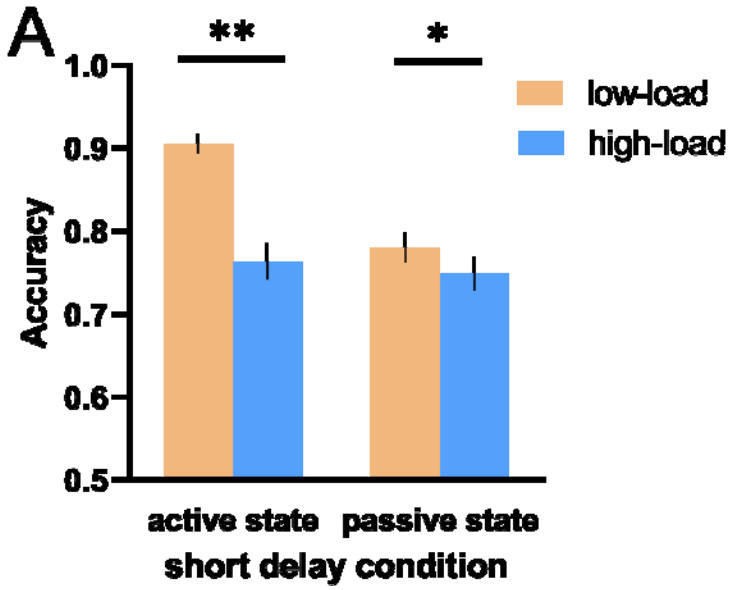
Method

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 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 retention was assessed in 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 delay condition was counterbalanced between subjects. The low- and high-load was randomly presented in each block with equal probability.



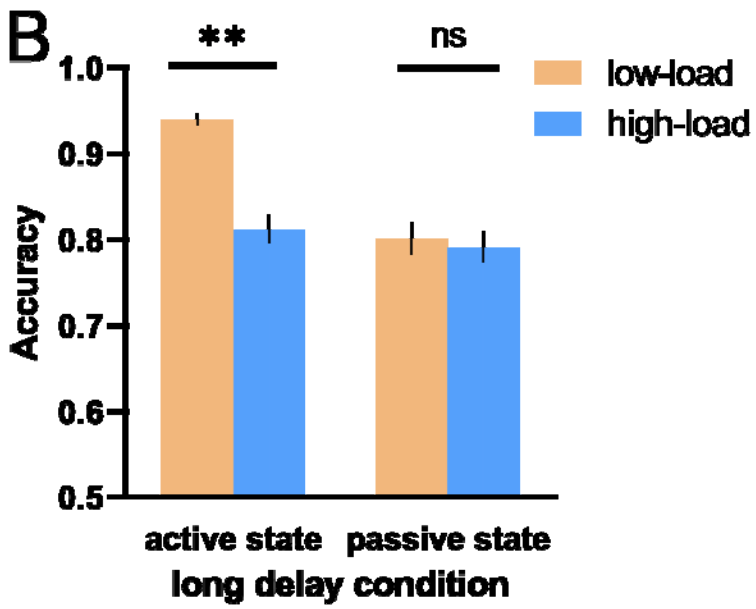


Figure 4: Mean accuracy of the active and passive states in short (A) and long (B) delay conditions in Experiment 3. Error bars indicate the standard error.

Results

The data across all participants were subject to the same analysis plan as 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 that in previous experiments, showing an effect of active load variation on the passive representations.

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 effect of active load variation on the passive representations. We then conducted a 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 sources of causing the overlap between representational transition and subsequent sensory processing.

Discussion

These results suggested that the representational transition smoothly complete

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 the passive representations formed during the multiple states of VWM. To this end, we adopted a sequential presentation paradigm to identify whether there was representational transition when the active format of 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 this issue. To rule out the effect of unpredictability of 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 the passive representation were consciously formed via 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 have come to the conclusion that the passive representation was consciously formed via representational transition from the active state according to the task demands.

The current results in fact fall in with resources-dissociation account of VWM (Li et al., 2021; Oberauer, 2002). Notably, the time frame for stimuli events played a critical role in multistate maintenance of 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 could 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 time 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 the neuropsychological perspective. With regard to 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 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. Due to the fact that the pattern of short-term synaptic plasticity underlay both the passive maintenance and the long-term memory

maintenance, the transition manner for the passive representations has the implication that handing off the memory representations into the passive state benefited to 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 enlightenment about optimizing the long-term memory maintenance in mind.

In the current study, we proposed that the state transformation of memory representations unfolded 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 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 study. In terms of the 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). In addition, 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 the cognitive demands. In addition, the memory representations

transitioned to the passive state in a strategic manner according to the task context. To conclusion, these findings have elucidated that the passive representations were consciously formed via a top-down process.

Conclusion

In summary, the passive representations were consciously formed via a transition process from the active to the passive state. The current results implied that, at the neural level, the active format of memory representation did not accompany its passive format underling the passive maintenance. We have come to the conclusion that the passive maintenance for a short time contributes to the synaptic pattern of memory maintenance. This perspective inspired us to propose that the passive maintenance of memory representations could boost their performance in long-term memory.

Acknowledgement

This research was supported by grants from 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, A., & 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

Johanna Kreither, O. P. and S. J. L. (2021). *Active working memory and simple cognitive operations*. *1*(530). https://emea.mitsubishielectric.com/ar/products-solutions/factory-automation/index.html

Kamiński, J., & Rutishauser, U. (2020). Between persistently active and activity-silent frameworks: novel vistas on the cellular basis of working memory. *Annals of the New York Academy of Sciences*, *1464*(1), 64–75. https://doi.org/10.1111/nyas.14213

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

LaRocque, J. J., Lewis-Peacock, J. A., & Postle, B. R. (2014). Multiple neural states of representation in short-term memory? It's a matter of attention. In *Frontiers in Human Neuroscience* (Vol. 8, Issue JAN, pp. 1–14). https://doi.org/10.3389/fnhum.2014.00005

Lewis-Peacock, J. A., Drysdale, A. T., Oberauer, K., & Postle, B. R. (2012a). Neural evidence for a distinction between short-term memory and the focus of attention. *Journal of Cognitive Neuroscience*, *24*(1), 61–79. https://doi.org/10.1162/jocn_a_00140

Lewis-Peacock, J. A., Drysdale, A. T., Oberauer, K., & Postle, B. R. (2012b). 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

Manohar, S. G., Zokaei, N., Fallon, S. J., Vogels, T. P., & Husain, M. (2019). Neural mechanisms of attending to items in working memory. *Neuroscience and Biobehavioral Reviews*, *101*(March), 1–12. https://doi.org/10.1016/j.neubiorev.2019.03.017

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. (2008). 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., & Lange, E. B. (2009). Activation and binding in verbal working memory: A dual-process model for the recognition of nonwords. *Cognitive Psychology*, *58*(1), 102–136. https://doi.org/10.1016/j.cogpsych.2008.05.003

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

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

Widhalm, M. L., & Rose, N. S. (2019). How can transcranial magnetic stimulation be used to causally manipulate memory representations in the human brain? *Wiley Interdisciplinary Reviews. Cognitive Science*, *10*(1), e1469. https://doi.org/10.1002/wcs.1469

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*.