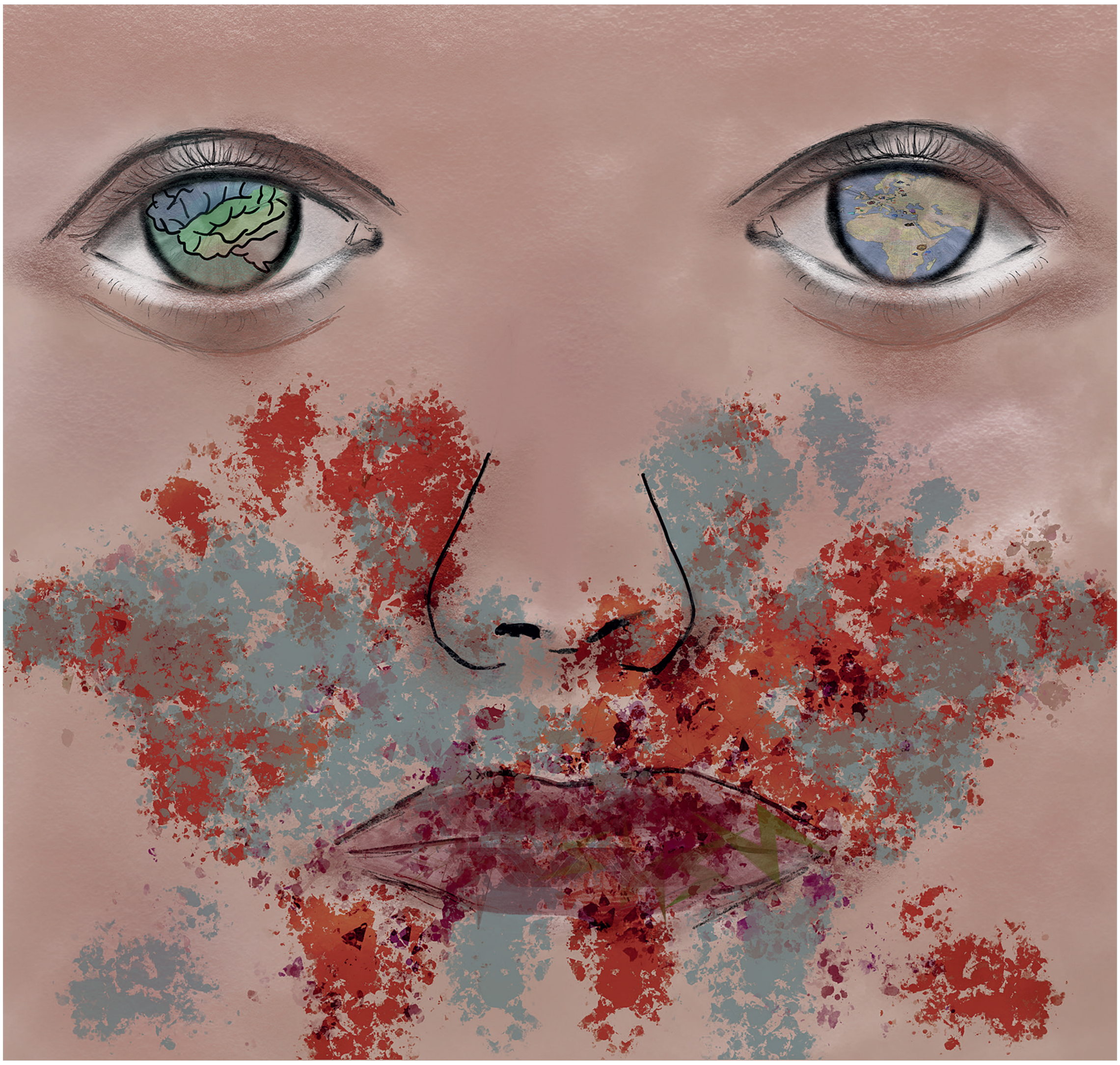
JYU DISSERTATIONS 338

Chaoxiong Ye

Visual Working Memory Resource Allocation is Affected by Stimulus-Related and Individuals' State- and Trait-Related Factors



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Esitetään Jyväskylän yliopiston kasvatustieteiden ja psykologian tiedekunnan suostumuksella
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ABSTRACT

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Visual working memory (VWM) is a system to actively maintain visual information to meet the needs of ongoing cognitive tasks. There is a trade-off between the precision of each representation stored in VWM and the number of representations due to the VWM resource limit. VWM resource allocation can be studied in two ways: one way is to investigate the ability to voluntarily trade off VWM precision and representation number stored in VWM; the other way is to investigate the ability to filter task-irrelevant information. The factors that influence these two aspects remain unclear. I investigated the influence of stimulus presentation time, VWM capacity, and emotional state on this trade-off ability attributed to VWM (**Study I** and **Study II**). In addition, I investigated the influence of facial expression of distractor stimuli, VWM capacity, and depressive symptoms on filtering ability (**Study III** and **Study IV**). **Study I** demonstrated that there is a positive relationship between VWM capacity and voluntary trade-off ability only when stimulus presentation time is long. **Study II** found that participants can improve VWM precision in a negative emotional state by reducing the number of representations stored in VWM when the stimulus presentation time is long. **Study III** found that face distractors could be filtered by participants with high VWM capacity, while low capacity participants had difficulties in filtering both angry and neutral face distractors. **Study IV** found that dysphoric participants could filter both sad and fearful face distractors. In contrast, non-dysphoric participants failed to filter fearful face distractors, but they could filter sad face distractors efficiently. Overall, the results of these studies suggest that VWM resource allocation is affected by stimulus-related and individuals' state- and trait-related factors (i.e., stimulus presentation time, VWM capacity, emotional state, facial expression, and depressive symptoms). These findings provide a better understanding of VWM resource allocation, which can possibly be applied in the future when developing methods for cognitive training and clinical purposes.

Keywords: brain’s event-related potentials, emotional faces, emotional state, memory capacity, stimulus presentation time, visual working memory

TIIVISTELMÄ (FINNISH ABSTRACT)

Ye, Chaoxiong
Visuaalisen työmuistin resurssit: ärsykkeiden ja yksilön tilan ja piirteiden vaikutus
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Visuaalinen työmuisti on systeemi, jota käytetään ylläpitämään näköinformaatiota muistissa, jotta pystytään vastaamaan meneillään olevien kognitiivisten tehtävien tarpeisiin. Koska visuaalisen työmuistin resurssit ovat rajalliset, on tehtävä kompromissi jokaisen työmuistiin tallennettavan edustuksen tarkkuuden ja edustuksien määrän välillä. Visuaalisen työmuistin resurssien suuntaamista voidaan tutkia kahdesta näkökulmasta: toinen on tutkia kykyä kohdentaa resurssit tehtävän kannalta oleelliseen informaatioon, ja toinen on tutkia kykyä suodattaa tehtävälle epäoleellista tietoa. On kuitenkin epäselvää, mitkä tekijät vaikuttavat kykyyn kohdentaa työmuistiresursseja. Tässä väitöskirjatutkimuksessa selvitin ärsykkeen esittämisajan, yksilöllisen visuaalisen työmuistin kapasiteetin ja tunnetilan vaikutusta työmuistiin liittyvään kompromissikykyyn (osatutkimukset I ja II). Lisäksi tutkin häiritsevien ärsykkeiden tunnepitoisuuden, yksilöllisen työmuistikapasiteetin ja masennusoireiden vaikutusta kykyyn suodattaa tietoa työmuistista (osatutkimukset III ja IV). Tutkimus I osoitti, että visuaalisen työmuistikapasiteetin ja omaehtoisen kompromissikyvyn välillä on yhteys vain silloin kun ärsykkeen esittämisaika on pitkä. Tutkimus II taas osoitti, että negatiivinen tunnetila vaikuttaa kompromissiin työmuistin tarkkuuden ja edustusten määrän välillä, kun ärsykkeen esittämisaika on pitkä. Tutkimus III osoitti, että ihmiset, joilla on suuri työmuistikapasiteetti, kykenevät suodattamaan epäoleellisia kasvokuvia työmuistista, kun taas niillä, joilla on pieni työmuistikapasiteetti, on vaikeuksia suodattaa neutraaleja ja vihaisia kasvoja. Tutkimus IV osoitti, että tutkittavat, joilla on masennusoireita, kykenevät suodattamaan työmuistista häiritseviä surullisia ja pelokkaita kasvoja. Sen sijaan kontrollikoehenkilöt epäonnistuivat pelokkaiden kasvojen suodattamisessa. Tämän väitöskirjan tulokset osoittavat, että visuaalisen työmuistin resurssien kohdentaminen on riippuvainen sekä yksilön tilaan ja piirteisiin liittyvistä tekijöistä, että ärsykkeisiin liittyvistä tekijöistä. Tulokset lisäävät ymmärrystämme visuaalisen työmuistin resurssien jakamisesta, ja niitä voidaan mahdollisesti käyttää tulevaisuudessa kehitettäessä menetelmiä kliinisiin tarkoituksiin.

Avainsanat: Tunnepitoinen tieto, aivojen herätevasteet, muistikapasiteetti, ärsykkeen esitysaika, visuaalinen työmuisti

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This journey is coming to an end. In May 2018, I completed my first PhD in cognitive science in two years and seven months. In August 2018, I started this new journey. People have repeatedly asked me this question: "Why do you want to get a second PhD?" I am fully aware that doing so may not bring much benefit to my academic career, so my general answer is "because I can". In fact, there are other unrealistic reasons in my heart to push me to do this. One of them is that in this book—a place of profound significance in my life—I am able to freely thank many people who have been important to me during this time.

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LIST OF ORIGINAL PUBLICATIONS

I Ye, C., Sun, H., Xu, Q., Liang, T., Zhang, Y., & Liu, Q. (2019). Working memory capacity affects trade-off between quality and quantity only when stimulus exposure duration is sufficient: Evidence for the two-phase model. *Scientific Reports*, 9, 8727.

II Long, F. (co-first author), Ye, C. (co-first author), Li, Z., Tian, Y., & Liu, Q. (2020). Negative emotional state modulates visual working memory in the late consolidation phase. *Cognition and Emotion*, 34, 1646-1663.

III Ye, C., Xu, Q., Liu, Q., Cong, F., Saariluoma, P., Ristaniemi, T., & Astikainen, P. (2018). The impact of visual working memory capacity on the filtering efficiency of emotional face distractors. *Biological Psychology*, 138, 63-72.

IV Ye, C., Xu, Q., Li, X., Ruohonen, E. M., Liu. Q., & Astikainen, P. (2020). Efficient filtering of sad and fearful faces from working memory in dysphoria. Submitted manuscript.

The author contributed to the original publications listed above as follows: for all studies, the author, with valuable insight from all co-authors, conceived and designed the experiments, participated in or supervised research assistants in data gathering, analyzed the data, interpreted the results, and wrote the manuscripts.

FIGURES

CONTENTS

1 INTRODUCTION

In order to respond to the complex external world, humans must store visual content in a temporary storage buffer for efficient processing. Visual working memory (VWM) is an important mental storage system that can briefly store visual information, integrating information from external inputs to create dynamic and continuous experiences. After forming VWM representations, people can still mentally access and control them even if the external visual information disappears (Cowan, 2001; Luck & Vogel, 1997). An efficient VWM system enables people to select relevant information from a visual scene, store the information in a highly precise manner, and filter irrelevant information (Vogel et al., 2005). The studies in this book aim to investigate which aspects affect the VWM system by manipulating stimulus-related (e.g., stimulus presentation time, emotional content of stimulus) and individuals' state-related factors (e.g., emotional state). In addition, the effects of depressive symptoms on participants’ VWM capacity were investigated.

1.1 The VWM system

The VWM system is a crucial cognitive system that can actively maintain other advanced cognitive processes and provide them with sufficient visual information (Luck & Vogel, 2013; Ma et al., 2014). By providing a dynamic processing storage platform for humans (Fukuda, Vogel, et al., 2010; Ikkai et al., 2010), the VWM system enables humans to keep relevant visual information separate from the complex environment. By maintaining VWM representations after the visual scene disappears, the system acts as a gatekeeper between perception and advanced cognitive functions (Baddeley, 2012).

It is generally acknowledged that VWM capacity is extremely limited (Fukuda, Awh, et al., 2010). Some individuals can keep up to three to four simple items (e.g., colors) in VWM, whereas others can only keep one or two items (Vogel & Awh, 2008). In addition, these individual differences are closely related to many advanced cognitive functions. Positive correlations have been found between VWM capacity and basic aspects of advanced cognition (Johnson et al., 2013). Moreover, individual differences in VWM capacity can account for a large proportion of individual differences in fluid intelligence (Fukuda, Vogel, et al., 2010).

Previous studies have shown that people's VWM capacity develops in childhood, peaks in youth, and then declines with age (Brockmole & Logie, 2013; Brockmole et al., 2008). Moreover, there are significant differences in VWM capacity among different populations. For example, the VWM capacity of individuals with Parkinson's disease (Lee et al., 2010) and schizophrenia (Johnson et al., 2013; Lee & Park, 2005) is lower than that of healthy adults.

The visual system often encounters task requirements that exceed the limits of VWM. In such cases, the VWM system attempts to selectively keep the task-relevant information by improving the memory precision of targets and filtering out task-irrelevant distractors.

1.2 Theories of VWM resources

Since the VWM resources available to each individual are very limited, it is natural to ask what the nature of VWM is (Suchow et al., 2014). Two classes of models have been proposed to answer this question: discrete resource models and continuous resource models. The discrete resource models propose that VWM has a limited number of available "slots" that store a limited set of discrete, fixed-precision representations (Cowan, 2001; Luck & Vogel, 1997; Vogel et al., 2001). When all slots are filled, no information about additional items can be stored. If the number of to-be-represented items is below the maximum number of slots, then an item can be represented by multiple slots (Zhang & Luck, 2008). The discrete resource models have received support from a number of empirical studies (Balaban et al., 2019; Barton et al., 2009; Donkin et al., 2013; Rouder et al., 2008; Zhang & Luck, 2011). Alternatively, the continuous resource models propose that the VWM resource supporting VWM storage is better described as a type of continuous resource. These models do not impose an upper limit of representation number but propose VWM consists of a pool of resources that can be allocated flexibly to a small number of items to create high-precision representations or distributed among a large number of items to create low-precision representations (Bays et al., 2009; Bays & Husain, 2008; Bays, Wu, et al., 2011; Huang, 2010; Wilken & Ma, 2004). A recent continuous resource model, called the variable-precision model, proposes that the precision of VWM representations varies randomly from trial to trial (Fougnie et al., 2012; van den Berg et al., 2012). This model has been supported by several recent studies (Emrich et al., 2017; Veksler et al., 2017). The debate between the discrete resource models and continuous resource models has been intense and is still currently unresolved (Balaban & Luria, 2015; Bays, 2014, 2015; Franconeri et al., 2013; Luck & Vogel, 2013; Vogel & Machizawa, 2004); however, there is general agreement that the VWM is an allocable resource of a limited capacity. In addition, when the number of items to be memorized is below the upper limit of individual VWM capacity, discrete resource models and continuous resource models have similar predictions for VWM performance (i.e., memory precision decreases with an increase in the number of memory representations).

The current debate between these two classes of VWM models centers around the quantization in VWM. However, neither theory class makes it clear how the VWM is allocated to store items, regardless of the discrete or continuous nature of the VWM itself (Suchow et al., 2014). The mechanism of allocation addresses the general question of how people structure and process VWM representations, which is an important aspect of VWM that is not captured in the discrete resource vs. continuous resource debate (Brady et al., 2011; Johnson et al., 2014; Suchow et al., 2014).

1.3 Paradigms of VWM studies

It is generally believed that a VWM task contains at least three process stages (Ye, 2018). First, it is necessary to encode the target objects as psychological representations (perceptual representations) so that they can be processed and transmitted effectively. This kind of process occurs in an early stage of the VWM task, when a large number of memory items are proposed for inspection. Individuals can transmit perceptual representations to the VWM system, resulting in limited VWM representations. This process stage is called VWM consolidation. Second, the VWM representations must be maintained in the VWM in order to access it after the visual input has been taken away. This process stage is called VWM maintenance. Third, stored representations need to be able to be retrieved to complete a follow-up task. One example would be to compare them with the test stimuli to recognize the reappearance of previously seen items (e.g., a change detection task) or to recall one of the memory items (e.g., a recall task). This process stage is called VWM retrieval.

Three experimental paradigms are commonly used in VWM research: a change detection task, a lateralized change detection task, and a recall task. Of these, the change detection task is widely used in behavioral studies as it can determine whether the participants remembered the target stimuli (Luck & Vogel, 1997). The lateralized change detection task is similar to the change detection task, but it can also observe electroencephalography (EEG) indicators that track the maintenance of VWM in addition to behavioral indicators (Vogel & Machizawa, 2004). Through the change detection task and the lateralized change detection task, researchers can examine the number of items participants can memorize. In the recall task, researchers can not only measure the number of VWM representations but also quantify the precision of the VWM representations (Wilken & Ma, 2004; Zhang & Luck, 2008). Through this task, researchers are able to examine VWM precision and the relationship between quality and quantity of VWM representations.

1.3.1 Change detection task

The change detection task is widely used in VWM research (Luck & Vogel, 1997, 2013). In an example of a color change detection task, each trial includes four stages: fixation, memory array, blank interval, and test array (Figure 1a). Participants are asked to remember some items (e.g., colors) in the memory array and to detect any changes in the test array. Specifically, the participants need to indicate whether the items in the test array are the same as the items in the memory array.

By calculating the behavioral indicators (e.g., accuracy) for different memory arrays, researchers can obtain the VWM performance of participants for the corresponding memory stimuli.

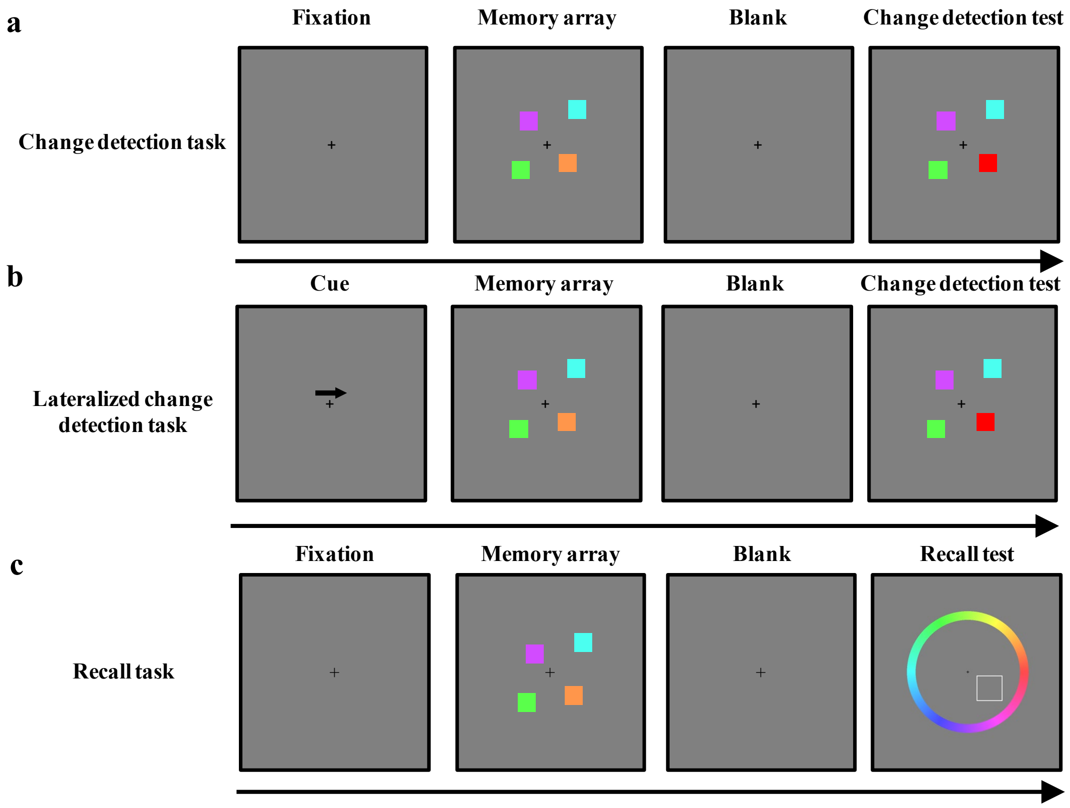

FIGURE 1 Concept of the (a) change detection task, (b) lateralized change detection task, and (c) recall task.

1.3.2 Lateralized change detection task

Early behavioral studies of VWM widely used the change detection task to measure VWM performance (Luck & Vogel, 1997, 2013). The change detection task requires participants to indicate whether the objects in the test array have changed. A potential problem in the change detection task is that participants must complete various cognitive processes during the task, including the decision-making process. Thus, the behavioral indicators could be affected by factors other than VWM (e.g., decision-making process).

Direct observation of brain activity is an effective way to avoid this potential problem. Using electroencephalography (EEG), event-related potentials (ERPs) can be averaged from an EEG signal that is time-locked to a memory stimulus. The ERP component can track VWM maintenance without being affected by other processes (e.g., the decision-making process). In order to detect such brain activity, Vogel and Machizawa (2004) developed a lateralized change detection task to identify ERP components related to VWM maintenance. As shown in Figure 1b, the lateralized change detection task is similar to the change detection task, but participants are only required to memorize the lateral stimuli in the cued visual hemifield (attended side). Thus, the ERP difference between the attended and non-attended sides can be observed in the lateralized change detection task. Vogel and Machizawa (2004) found that after the memory stimulus disappears, there is a negative slow difference wave in the VWM maintenance phase. Importantly, the amplitude of this difference wave increases as the number of objects stored in the VWM increases. When the number of items stored in the VWM reaches the limit of an individual's VWM capacity, the amplitude of the difference wave approaches an asymptote. This ERP component is defined as contralateral delay activity (CDA). When participants keep more representations in their VWM system, a larger CDA amplitude can be observed. Therefore, the CDA component is widely used as an ERP marker of the number of items stored in VWM (Adam et al., 2018; Feldmann-Wustefeld & Vogel, 2019; Feldmann-Wustefeld et al., 2018; Fu et al., 2020; Hao et al., 2018; Li et al., 2020; Liang et al., 2020; Luria et al., 2016; McCollough et al., 2007; Vogel & Machizawa, 2004; Vogel et al., 2005; Xue et al., 2015; Ye et al., 2014).

1.3.3 Recall task

Although most VWM studies require participants to use change detection tasks to determine whether memory items have changed in order to measure VWM performance (Luck & Vogel, 1997, 2013), a new VWM task was developed using a different test procedure. Wilken and Ma (2004) asked their participants to recall colors in their VWM by selecting a color on a color wheel. This paradigm is called the recall task, and it has been widely used in studies to explore issues related to VWM precision. One example of a recall task has four stages: fixation, memory array, blank interval, and recall array (Figure 1c). Participants are asked to remember several items in the memory array and recall the value of one memory target. When the recall array appears, they need to recall the value of the target item (e.g., select the color of the item from a color wheel).

Using the recall task, researchers have developed suitable models for fitting the recall response distribution, allowing the number of representations in VMW and memory precision to be measured separately. Researchers calculated the difference between the target object and the recalled object (recall error) in each trial. A "mixture model" proposed by Zhang and Luck (2008) could explain the recall error results. The mixture model consists of the contributions from two different types of trials: random response and response to VWM representations. In random response trials, participants are not able to store the target representations in VWM, so they can only guess and respond randomly. The recall error results of random response trials conform to continuous uniform distribution. In the response trials to the VWM representations, internal noise can cause participants to form noisy target memory. The recall error results of such trials conform to a von Mises distribution. The mixture model can be described by the following formula:

$$p(\hat{\theta}) = (1-\gamma)\Phi_{\sigma}(\hat{\theta}-\theta) + \gamma\frac{1}{2\pi},$$

where θ refers to the value of the target item, $\hat{\theta}$ refers to the recalled value, γ refers to the proportion of random response trials, and Φ_{σ} refers to the von Mises distribution with a standard deviation (SD) σ.

By fitting the recall error data through maximum likelihood estimation, researchers can quantify memory precision (SD^{-1}) and memory rate (P) based on the recall response results. For instance, the p value (1−γ) is the proportion of responses to target memory. The SD value (σ) is the circular standard deviation of the von Mises distribution, which is inversely proportional to the precision of stored VWM representations. This method expands VWM research from exploring the general performance of VWM to exploring the precision of VWM representations. This also provides the possibility of further investigating the trade-off between VWM precision and the number of stored VWM representations.

Later, unlike in the mixture model, Bays et al. (2009) proposed a swap model with an extra component, non-target responses, to explain the offset results. In addition to the two components of the mixture model, Bays et al. (2009) suggested that there was a certain possibility participants would confuse the representation of memory, making a mistake and responding to the non-target representation as the target. In the trials with non-target responses, participants reported the results conforming to a von Mises distribution centered on the value of one of the non-target items. Both mixture and swap models can quantify memory rate and memory precision of the participants. Besides these two models, a variable-precision model was proposed and suggests that the precision of VWM representations varies randomly from trial to trial (Fougnie et al., 2012; van den Berg et al., 2012). Although much evidence supports that the variable-precision model can better account for the data (van den Berg et al., 2014), only the mixture model and the swap model can quantify memory rate and memory precision separately for research purposes.

1.4 Trade-off between VWM precision and number

Since VWM resources are limited, there is a trade-off between the memory precision of each representation stored in VWM and the number of representations. Using the change detection task, Alvarez and Cavanagh (2004) asked participants to memorize different types of objects, ranging from simple to complex (i.e., colors, letters, lines, Chinese characters, random polygons, and shadow cubes). By systematically manipulating the information that had to be remembered for each object, they found that the limit on the number of VWM representations depended on the complexity of the objects that needed to be remembered. Participants can remember fewer complex objects than simple objects. To maintain complex objects in VWM, participants needed to use higher VWM precision in order to detect whether these objects had changed compared to the test array in the change detection task. Therefore, when the VWM precision of the stored object was higher (i.e., when remembering complex objects), participants could store fewer objects in their VWM. Since the VWM system can only store limited visual information, their results suggest that the number of VWM representations is negatively correlated to the precision of VWM representations. Similarly, using the recall task to directly measure VWM precision, Wilken and Ma (2004) suggested a trade-off between the VWM number and VWM precision. They found that VWM precision decreases as the VWM number increases.

These studies demonstrate that the VWM system does not hold a fixed number of representations with fixed precision. Instead, the precision of each VWM representation depends on how many resources can be allocated to the representation from the limited resources shared between representations. Therefore, individuals can maintain a single representation with high VWM precision, but can only maintain multiple objects with lower precision. In the last two decades, many behavioral and ERP studies have analyzed the trade-off between VWM number and VWM precision (Bays et al., 2009; Bays & Husain, 2008; Gao et al., 2009; Luria et al., 2010; Zhang & Luck, 2008). Researchers can infer the VWM resource allocation mechanism by investigating the trade-off pattern between VWM precision and the VWM number. Previous studies have suggested that there are two possible methods for allocating VWM resources (Machizawa et al., 2012; Murray et al., 2012). Allocation can be driven by stimuli (e.g., number of items to memorize) or voluntary control factors (e.g., task requirement). I term the former the involuntary allocation hypothesis. It predicts that the precision of VWM representations is not affected by task requirements, but only by stimulus-driven factors (e.g., number of items to memorize). I term the latter the voluntary allocation hypothesis. It predicts that the precision of VWM representations can be voluntarily adjusted according to the requirements of the task.

Both the involuntary and voluntary hypotheses are supported by previous studies (Gao et al., 2011; He et al., 2015; Machizawa et al., 2012; Murray et al., 2012; Ye et al., 2014). For instance, Murray et al. (2012) manipulated a payment scheme to emphasize either VWM precision or VWM number. They found that VWM precision was only affected by the number of items to memorize (i.e., set size of memory items), not by the task requirements. This result supports the involuntary allocation hypothesis. In addition, some ERP studies also support the involuntary allocation hypothesis (He et al., 2015; Ye et al., 2014). In contrast, Machizawa et al. (2012) manipulated VWM precision through task requirements. They found that participants could voluntarily improve VWM precision based on task requirements only when the number of items to memorize was small. These results support the voluntary allocation hypothesis. The ERP study of Gao et al. (2011) also supported the voluntary allocation hypothesis.

The involuntary allocation and voluntary allocation hypotheses may not be mutually exclusive. The aforementioned research supporting involuntary allocation used a relatively short memory array presentation time of approximately 25–50 ms/item (He et al., 2015; Murray et al., 2012; Ye et al., 2014). In contrast, studies that support the voluntary allocation hypothesis tend to use a relatively long memory array presentation time of approximately 100–125 ms/item (Gao et al., 2011; Machizawa et al., 2012).

Since it has been found that the memory array presentation time affects the VWM resource allocation process (Bays, Gorgoraptis, et al., 2011; Ye, Liang, et al., 2020), I proposed a two-phase VWM resource allocation model to explain the evidence supporting the involuntary and voluntary allocation hypotheses (Ye, 2018; Ye et al., 2017). The two-phase model implies that when visual information is consolidated in VWM, resource allocation occurs in two phases. In the early phase of VWM consolidation, people cannot predict the length of presentation time when the external visual information is presented. Even if VWM precision is low, maintaining as many visual items as possible is conducive to survival. Therefore, VWM resources can only be automatically allocated to as many presentation items as possible in an involuntary manner when the presentation time of the memory array is short (in the early consolidation phase). This allocation strategy causes a fixed trade-off ratio between the VWM number and precision in the early consolidation phase. In other words, the trade-off ratio is not affected by the voluntary control factors; rather, it is determined by the stimulus-driven factor (e.g., number of items to memorize) in the early phase of VWM consolidation. The early phase of VWM consolidation is completed when people consolidate as many visual items as possible. Subsequently, the late phase of VWM consolidation begins. In this phase, if the visual information does not disappear, people can consolidate more new information into the VWM according to their own preferences or strategies to obtain VWM representations with higher precision. When a task requires participants to remember memory items in a highly precise way, they can reduce the number of VWM representations to free up VWM resources and then use those resources to enhance the VWM precision in the late consolidation phase. In other words, VWM resources can only be voluntarily allocated to either increase the VWM number or improve VWM precision according to the task requirement when the presentation time of the memory array is long (i.e., in the late consolidation phase). During this phase, the trade-off ratio can be adjusted as a result of individuals' preferences or strategies instead of stimulus-driven factors. Therefore, for a given number of items to memorize, a certain amount of consolidation time (i.e., presentation time of memory items) is required to adjust the trade-off between VWM precision and the VWM number.

The two-phase model can reconcile previous contradictory findings. The model also suggests that VWM research should recognize the presentation time of memory items as an important factor that affects the trade-off between VWM precision and the VWM number.

1.5 Distractor filtering in VWM

In addition to allocating resources to task-relevant representations, effective VWM resource allocation must avoid distributing resources to task-irrelevant distractors, which is the process of distractor filtering in VWM.

Previous studies suggest that the capability of distractor filtering is associated with individuals' VWM capacity (Jost et al., 2011; Owens et al., 2012; Vogel et al., 2005). Using the CDA component, Vogel et al. (2005) found that participants with high or low VWM capacity differ in their distractor filtering capability in the VWM task. They asked participants to remember two task-relevant items and ignore two task-irrelevant items. The results showed that participants with high VWM capacity could filter out the task-irrelevant items (distractors), while participants with low VWM capacity involuntarily stored task-irrelevant items in VWM. Cowan and Morey (2006) interpreted this result to indicate that effective VWM processing relies on effective attention filtering. In fact, many aspects of the interaction between working memory and attention have been widely investigated (Awh et al., 2006). For example, continuous visuospatial attention can improve the maintenance of a VWM representation after the disappearance of visual information (Chun, 2011; Liang et al., 2019). VWM representations can automatically guide selective attention in the visual search task (Lu et al., 2017; Soto et al., 2005). Attentional resources can improve the efficiency of VWM resource allocation (Zhang et al., 2018). In addition, the VWM and attention processes involve several common brain regions, such as the bilateral insula, the right occipital cortex, and the right frontal-parietal cortex (Anderson et al., 2010; Mayer et al., 2007). Common neural substrates could explain why VWM capacity and distractor filtering ability are interlinked. Further, Fukuda and Vogel (2009) corroborated that participants with high VWM capacity are more resistant to attention capture than participants with low VWM capacity. These studies demonstrate the key relationship between VWM capacity and distractor filtering ability in tasks with distractors (Fukuda & Vogel, 2009; Owens et al., 2012; Vogel et al., 2005).

However, not all studies support the relationship between VWM capacity and the ability to use internal attention. For example, recent finding from my group quantified the participant's ability to utilize internal attention by using the magnitude of retro-cue benefit. The results show that VWM capacity is not related to the magnitude of retro-cue benefits (Ye, Xu, Astikainen, et al., 2020). Therefore, in other tasks related to resource allocation, such as tasks that require a voluntary trade-off between VWM precision and the VWM number, the relationship between VWM capacity and trade-off ability remains unclear.

According to the two-phase VWM resource allocation model (Ye, 2018; Ye et al., 2017), it is reasonable to believe that the presentation time of the memory array that affects the trade-off may be related to participants' VWM capacity. Although many previous studies have investigated how participants can trade off VWM precision and the VWM number (i.e., flexibly adjust the trade-off between VWM precision and the number of stored VWM representations), the relationship between VWM capacity and trade-off ability has not been carefully studied (Bocincova et al., 2017; Fougnie et al., 2016; Gao et al., 2011; He et al., 2015; Machizawa et al., 2012; Murray et al., 2012; Ramaty & Luria, 2018; Ye et al., 2014; Zhang & Luck, 2011).

1.6 Effect of a negative emotional state on trade-off

In addition to VWM capacity, previous studies have shown that negative emotional states also affect VWM precision, the VWM number, and the trade-off between them. Several previous studies support the idea that negative emotional states can damage VWM performance. For example, using CDA, Figueira et al. (2017) investigated the impact of emotional states on VWM. They found that, in a neutral emotional state, participants can store four items in VWM, while in a negative emotional state, only two of four items can be maintained in VWM. Similar results were reported in a follow-up study (Figueira et al., 2018). These ERP results indicate that a negative emotional state can reduce the number of representations stored in VWM.

However, not all evidence indicates that only negative emotional states have a negative impact on VWM performance. For instance, Zhang et al. (2017) used movie clips to induce different emotional states in participants and then asked them to perform a change detection task. They found that both negative and positive emotional states enhanced VWM performance in the high VWM capacity group, while the VWM performance in the low VWM capacity group decreased. Therefore, in the change detection task, it may be difficult to observe the influence of emotional states on VWM performance among all participants. Notably, Figueira et al. (2017) found that based on CDA results participants' VWM number was reduced in a negative emotional state, but they found no significant difference in behavioral performance in the neutral or negative emotional state. These contradictory findings suggest that the behavioral indicators in the change detection task may not be sensitive to the influence of the emotional state on VWM representations. The number and precision of the representations stored in the VWM affect the accuracy. Since there is a trade-off relationship between VWM number and VWM precision, VWM precision decreases as VWM number increases and *vice versa* (Barton et al., 2009; Bays et al., 2009; Machizawa et al., 2012). In this case, changes in the trade-off ratio do not necessarily lead to changes in the accuracy results. Although accuracy increases as the accuracy of the VWM increases, it also decreases as the VWM number decreases. Therefore, when the VWM number decreases and VWM precision increases, a change in accuracy may not be observed. This can explain why Figueira et al. (2017) found no impact of a negative emotional state on accuracy. Because the CDA component mainly tracks the VWM number rather than VWM precision (Gao et al., 2011; but see Sessa et al., 2011). The contradiction between behavioral and ERP results may indicate that negative emotional states increase the precision of VWM representations while reducing the VWM number. Therefore, a negative emotional state may not simply harm VWM; it could also change the trade-off ratio between the VWM number and VWM precision.

A previous study supports this possibility. In order to investigate the impact of a negative emotional state on VWM, Spachtholz et al. (2014) used music and guided rumination to induce a negative emotional state and then asked participants to conduct a recall task. They found that, compared with neutral emotional states, negative emotional states reduced the number of representations stored in VWM, while VWM precision still increased. In other words, a negative emotional state changes the trade-off ratio between the VWM number and VWM precision.

However, not all studies using recall tasks demonstrate that negative emotional states affect the trade-off ratio between the VWM number and VWM precision. Xie and Zhang (2016) used negative pictures to induce a negative emotional state. They found that a negative emotional state can improve VWM precision without reducing the number of stored representations. In other words, they detected only benefits to a negative emotional state to VWM.

Based on the two-phase model (Ye, 2018; Ye et al., 2017), the presentation time of memory array affects whether participants can adjust the trade-off ratio between VWM precision and the VWM number in a top-down control manner. Therefore, it is worth exploring whether negative emotional states have different effects on VWM precision, the VWM number, and the trade-off between them a different stimulus presentation times.

1.7 Filtering of expression distractor in VWM

Most previous VWM studies used geometrical objects, such as colored squares and tilted lines, as stimuli (Luck & Vogel, 2013); however, the visual information we see in the real world is usually more complex and varied. For example, social and affective contents are also crucial for human cognition processing. It is crucial for us to understand how we manipulate this emotional information in our VWM.

Compared to other visual objects, faces more easily capture our attention and humans are experts at face perception (Ro et al., 2001; Vuilleumier, 2000; Young & Burton, 2018). Different expressions have different processing advantages (Xu et al., 2019; Xu et al., 2020); for example, angry faces convey threatening information that is particularly efficient at drawing attention (Fox et al., 2000; Hansen & Hansen, 1988; Pinkham et al., 2010). It has been suggested that VWM modulates face identification. For example, data from behavioral studies showed that participants could store more facial identities when the displayed faces were angry compared to happy or neutral, even if the emotional information was task-irrelevant (Jackson et al., 2014; Jackson et al., 2009). Thus, these studies suggested that angry faces not only have benefits in terms of attentional bias but also enhance VWM storage for facial identities.

VWM studies on expressions have recently expanded from memory maintenance to distractor filtering (Stout et al., 2015; Stout et al., 2013). Stout et al. (2013) used CDA to study task-irrelevant fearful face filtering efficiency. In this study, participants were asked to remember the identity of a neutral target face and ignore a distractor (i.e., a fearful or a neutral face). The results showed that fearful distractor faces induced a significantly larger CDA amplitude compared to the no distractor stimulus condition (one-target condition). However, there was no difference in CDA amplitude between the neutral distractor stimulus condition and the one-target condition (Stout et al., 2013). Their results suggested that fearful faces, not neutral faces, can automatically be stored in VWM, even when they are the distractors and are irrelevant to the current tasks. Hence, the emotional information of distractors affects the filtering efficiency. However, to my surprise, there are no studies that have investigated filtering processing with expressions other than fearful and neutral faces. Moreover, while many studies have investigated the filtering efficiency of various simple neural distractors (colors or orientations as target features, Owens et al., 2012; Vogel et al., 2005), little is known about the relation between VWM capacity and the ability to filter expression distractors.

1.8 Depression and distractor filtering

Depression is a severe multifaceted disorder that includes cognitive, physiological, and affective symptoms. It has been suggested that cognitive depressive symptoms include attention and concentration deficits (Mohanty & Heller, 2002) and may arise from fundamental executive dysfunction (Levine et al., 2007). According to Beck's cognitive theory of depression (Beck, 1967, 2008), depressed individuals have negative schemas that skew their information processing toward negative information. In research on attention, attentional bias toward negative information (e.g., sad faces) has been widely demonstrated for both attentive (for a review, see Dai & Feng, 2012; Gotlib &

Joormann, 2010) and pre-attentive perception (Ruohonen et al., 2020; Xu et al., 2018; Zhang et al., 2016; Zhao et al., 2015). Meanwhile, in VWM research, negative emotional states induced by negative stimuli have also been linked to VWM impairment. For example, using CDA in a change detection task, Figueira et al. (2017) found that participants could retain more colored squares in a neutral emotional state than in a negative emotional state. Similarly, in a study of differently depressed participants, a VWM bias toward sad faces (better VWM performance) compared to other expressions was reported in the melancholic depression group, but not in the control or non-melancholic depression groups (Linden et al., 2011). However, studies have also shown that depressed individuals with high suicidal intentions tend to maintain fewer negative faces in VWM compared to controls and individuals with low suicidal intentions (Xie et al., 2017). These studies indicate that depressed individuals show an overall attentional and VWM bias toward negative information; however, other factors, such as suicide-related risk, can also be modulatory.

Recently, it has been reported that dysphoric (elevated amount of depressive symptoms) participants performed worse at filtering irrelevant neutral geometric objects and showed reduced VWM capacity compared to non-dysphoric participants (Owens et al., 2012; Owens et al., 2013). However, how emotion distractor filtration in VWM is affected by depression/dysphoria remains unclear.

1.9 Purpose of the research

The purpose of my studies was to explore which factors affect the trade-off between VWM precision and number of representations stored in VWM (**Study I a**nd **Study II**) and the filtering of facial expression distractors in VWM (**Study III** and **Study IV**).

Study I investigated whether the voluntary trade-off ability between the VWM number and VWM precision varies based on VWM capacity. Using a recall task, I examined whether participants with different VWM capacity levels could voluntarily trade off the VWM number and VWM precision according to the task requirement in conditions with different memory array presentation times. Based on the two-phase VWM resource allocation model (Ye, 2018; Ye et al., 2017), I expected to find different impacts of VWM capacity on the voluntary trade-off ability depending on memory array presentation time.

Study II investigated whether a negative emotional state affects VWM precision, the VWM number, and the trade-off between them under different memory array presentation times. I expected that participants would increase VWM precision by sacrificing the VWM number when memory array presentation times were long.

Study III investigated the relationship between VWM capacity and the filtering of three expression distractors (neutral, angry, and happy) in a VWM task. I expected that participants with low VWM capacity would be less efficient at filtering neutral face distractors than participants with high VWM capacity. Moreover, participants would have more difficulty filtering out angry face distractors than happy face distractors.

Study IV investigated the relationship between depressive symptoms and the filtering of negative face distractors in the VWM task. Dysphoric and control participants with similar VWM capacities were compared. I expected that participants in the control group would unnecessarily store fearful face distractors into VWM. The level of unnecessary memory storage of fearful face distractors was expected to be similar between the dysphoric and control groups. The filtering of sad face distractors was expected to be more efficient than the filtering of fearful face distractors in the control group, as threat perception is prioritized for evolutionary reasons in human information processing. In the dysphoric group, I expected that their negative bias would lead to unnecessary storage of sad face distractors.

2 METHODS

2.1 Participants

Four different samples of adults were used: 52 healthy participants in **Study I**; 100 healthy participants in **Study II**; 42 healthy participants in **Study III**; and 48 participants with or without depressive symptoms in **Study IV**. All of the participants reported normal or corrected-to-normal vision, no history of neurological disease or brain operations, and no current substance abuse.

For **Study I**, 52 healthy Chinese adults were recruited from the participant pool of Liaoning Normal University. Twenty-six participants (age range = 18–22 y; mean = 21.2 y; SD = 1.0 y; 5 males and 21 females) were recruited for Experiment 1 and 26 new participants (age range = 19–24 y; mean = 21.0 y; SD = 1.1 y; 3 males and 23 females) were recruited for Experiment 2.

For **Study II**, 100 healthy Chinese adults were recruited from the participant pool of Liaoning Normal University. Thirty-three participants (age range = 19–23 y; mean = 21.3 y; SD = 1.2 y; 13 males and 23 females) were recruited for Experiment 3, 32 new participants (age range = 18–23 y; mean = 20.9 y; SD = 1.1 y; 12 males and 20 females) were recruited for Experiment 4, and 35 new participants (age range = 18–25 y; mean = 21.5 y; SD = 1.2 y; 13 males and 22 females) were recruited for Experiment 5.

For **Study III**, 42 healthy Chinese adults (10 males and 32 females) were recruited from the participant pool of Liaoning Normal University. After excluding participants with excessive artifacts in the EEG data, data on 32 participants (9 males and 23 females) remained for the final analyses. The mean age of the participants was 21.7 y (SD = 2.1 y).

For **Study IV**, 48 Finnish participants were recruited via email lists, web page announcements, and notice board announcements at the University of Jyväskylä for the two groups: dysphoric and control (non-dysphoric) groups. The inclusion criterion for the control group was a score of nine or less on the

Beck's Depression Inventory-II (BDI-II; Beck et al., 1996) and a score of 14 or higher on the BDI-II for the dysphoric group. The inclusion criteria for the study were normal or corrected-to-normal vision, right-handed, and age between 18 and 40 y. Participants with brain damage, neurological disorders, or a history of drug and/or alcohol abuse were excluded. The exclusion criteria for all participants were self-reports of neurological disorders (except migraine that was not recently active or fibromyalgia), current substance abuse, or brain damage. The exclusion criteria for the control group were a self-reported current or previous diagnosis of depression, any other psychiatric diagnosis, and current use of a medication that could affect the central nervous system. These criteria were investigated through a phone interview and questionnaires.

After excluding participants with excessive artifacts in the EEG data, data on 18 dysphoric participants (7 males and 11 females) and 18 control participants (4 males and 14 females) remained for the final analyses. The mean age of the dysphoric participants was 30.9 y (SD = 7.1 y) and the mean age of the control participants was 26.6 y (SD = 6.3 y).

All procedures in the experiments described herein were conducted in accordance with the Declaration of Helsinki (2008). Ethical approval was obtained from the Ethical Committee of the Liaoning Normal University for **Study I**, **Study II**, and **Study III** and from the Ethical Committee of the University of Jyväskylä for **Study IV**. All participants volunteered and could withdraw their participation at any time without consequence. Written informed consent was obtained from each volunteer before the experiments took place. Information was disseminated to the participants through easy-to-understand letters. Data were collected and analyzed pseudonymously (key code separate from the data files) and stored anonymously in secured servers provided by the Liaoning Normal University and University of Jyväskylä.

2.2 Stimuli and procedure

In all studies, participants were seated in a chair in a dimly lit room to complete the tasks. They were instructed to avoid all additional body movements, facial expressions, talking, and excessive head movement to facilitate paying attention to the fixation during the tasks. The visual stimuli were presented on a computer using E-prime software on a monitor situated in front of the participant (approximately 60 cm in **Study I** and **Study II**, 70 cm in **Study III**, and 100 cm in **Study IV**). In **Study III** and **Study IV**, the participants' ERPs were measured during the main task.

Two experiments (Experiment 1 and Experiment 2) were included in **Study I**. The main tasks of Experiments 1 and 2 were similar: to remember four colors in a color recall task. The trial structures are depicted in Figure 2. In each trial, the memory array appeared after a fixation. The memory array consisted of four brightly colored squares drawn at four fixed locations. Participants needed to memorize the colors of the squares in a blank interval. During the test, an outlined cue was presented at the location of one of the colored squares in the memory array. Participants needed to choose a color from the color wheel to indicate the color of the remembered square at the location of the outline. Then, feedback about the responses was presented. The feedback included the difference (offset) between the reported color and the color in the memory array. The scores earned were based on the participants' responses. By manipulating the reward scheme, participants were encouraged to remember colors in a low- or high-precision manner to earn better scores under the different precision conditions. Similar controls have also been used in previous studies (Ye et al., 2017; Zhang & Luck, 2011). The low-precision and high-precision conditions were blocked with the order counterbalanced across participants. Participants fully understood the rules of the reward scheme in each precision block before performing the task. Participants completed 280 trials for each precision condition. The only difference in procedure between Experiment 1 and Experiment 2 was that the presentation time of the memory array in Experiment 1 (500 ms) was longer than that of Experiment 2 (200 ms).

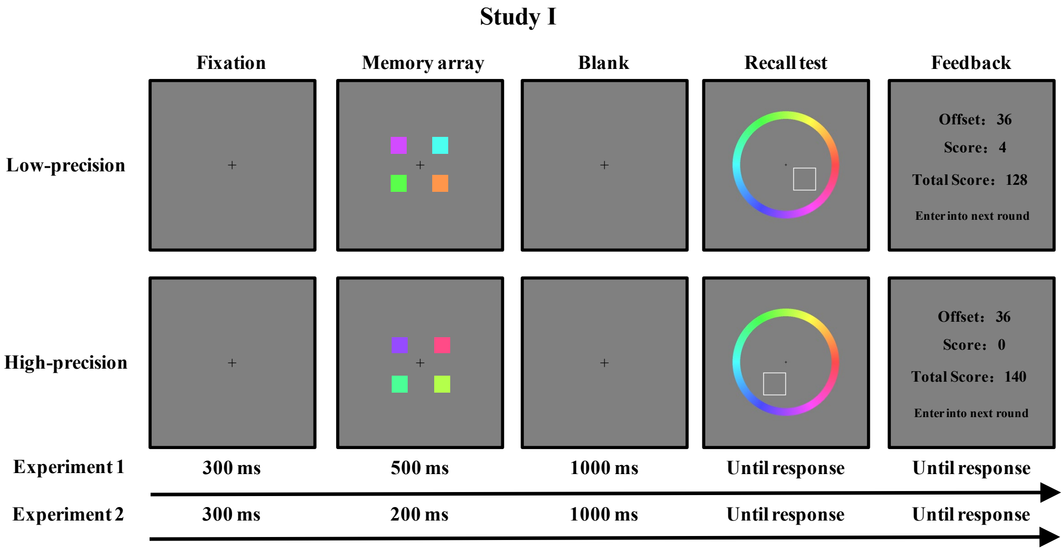

FIGURE 2 The trial structure of Experiments 1 and 2 in **Study I**. The low-precision condition and the high-precision condition with different presentation periods of the memory array are illustrated (500 ms for Experiment 1; 200 ms for Experiment 2). The figure is modified from Ye et al. (2019).

Three experiments (Experiment 3, Experiment 4, and Experiment 5) were included in **Study II**. The main tasks of Experiments 3, 4, and 5 were similar: to complete a valence judgment task for emotion induction and then remember the orientations of four gratings in an orientation recall task. The trial structures are depicted in Figure 3. In each trial, a neutral or negative image from the International Affective Picture System (IAPS) was presented. The emotion induction was similar to that of the previous studies (Xie & Zhang, 2016, 2017). Participants needed to choose a valence of the image on the nine-point

Self-Assessment Manikin (SAM) scale. Then, the memory array appeared after a blank delay period. The memory array consisted of four oriented gratings. Participants were instructed to remember the orientations of the gratings across a blank interval. During the test, an outlined cue appeared at the location of one of the oriented gratings in the memory array. Participants needed to adjust the orientation of a central grating to match that of the cued grating. The neutral emotional state and negative emotional state conditions were blocked, with the order counterbalanced across participants. The only difference in the procedure between Experiment 3 and Experiment 4 was the presentation time of the memory array in Experiment 4 (500 ms) was longer than Experiment 3 (200 ms). The procedure of Experiment 5 was similar to that of Experiments 3 and 4, except that the same group of participants needed to complete the tasks with both short (200 ms) and long (500 ms) presentation times of the memory array.

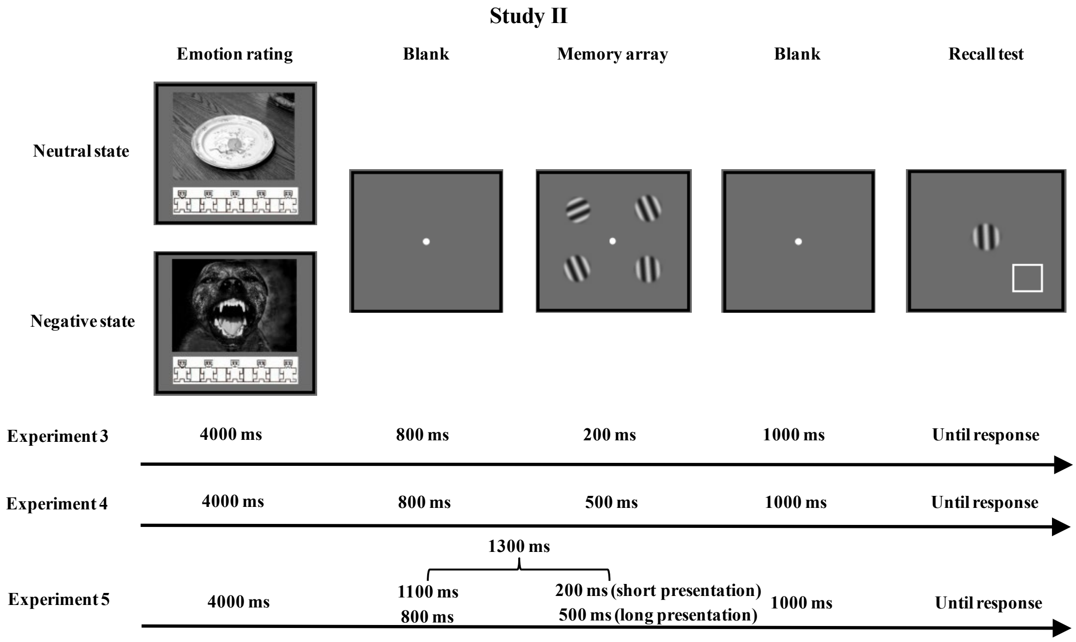

FIGURE 3 The trial structure of Experiments 3, 4, and 5 in **Study II**. A neutral emotional state condition and a negative emotional state condition with short and long memory array presentation periods are illustrated (200 ms for Experiment 3; 500 ms for Experiment 4; 200 ms or 500 ms for Experiment 5). The figure is modified from Long et al. (2020).

One experiment (Experiment 6) was included in **Study III**. The main task of participants in Experiment 6 was to remember target faces and ignore distractor faces in a lateralized facial change detection task. The trial structures are depicted in Figure 4. The stimuli were facial pictures of neutral, happy, and angry facial expressions chosen from the Chinese Facial Affective Picture System (CFAPS; Gong et al., 2011). In each trial, a pair of arrow cues appeared after a fixation. The cues both pointed either to the left or right. After a variable interval, the memory array appeared, consisting of one or two faces in each visual hemifield. The faces were surrounded by target or distractor frames with different colors (red or yellow). Participants were instructed to remember only the identities of target faces in the cued visual hemifield across a blank interval. During the test, a test array containing the same amount of faces as the memory array was presented. Participants needed to indicate whether there was a change in the target face identities. Seven memory array type conditions were included in the task: one neutral target face (1Nt); one neutral target face and one neutral distractor face (1Nt1Nd); two neutral target faces (2Nt); one neutral target face and one angry distractor face (1Nt1Ad); one neutral target face and one angry target face (1Nt1At); one neutral target face and one happy distractor face (1Nt1Hd); and one neutral target face and one happy target face (1Nt1Ht). Participants completed 160 trials for each memory type condition. EEG measurements were applied during the lateralized facial change detection task.

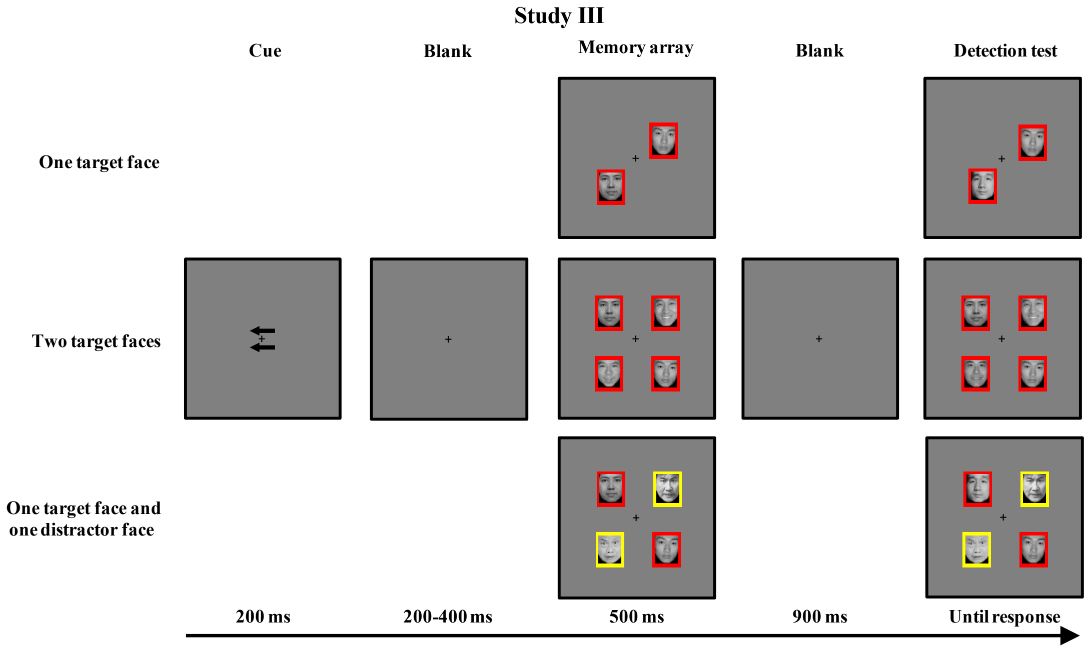

FIGURE 4 The trial structure of Experiment 6 in **Study III**. The red frames indicate target faces, and the yellow frames indicate distractor faces. Three memory type conditions (one target face, two target faces, one target face and one distractor face) are illustrated. Here, only trials with identity changes are depicted, but there were also trials without a change. The figure is modified from Ye et al. (2018).

One experiment (Experiment 7) was included in **Study IV**. The main task of participants in Experiment 7 was to remember target colors and ignore distractor faces in a lateralized facial change detection task. The trial structures are depicted in Figure 5. The distractor stimuli were facial pictures of sad and fearful facial expressions chosen from Ekman (1976)'s Pictures of Facial Affect. In each trial, a cue appeared after a fixation. The cues pointed either to the left or to the right. After a variable interval, the memory array appeared. The memory array consisted of two colored squares and/or one distractor face in each visual hemifield. Participants were instructed to remember only the colors of squares in the cued visual hemifield across a blank interval. During the test, a test array containing the same number of items as the memory array was presented. Participants needed to indicate whether there was a change in the colors. Three memory array type conditions were included in the task: the no distractor (Non-dis: only two colored targets); the fearful distractor (Fearful-dis: two colored targets and a fearful distractor); and sad distractor (Sad-dis: two colored targets and a sad distractor). EEG measurements were applied during the lateralized facial change detection task.

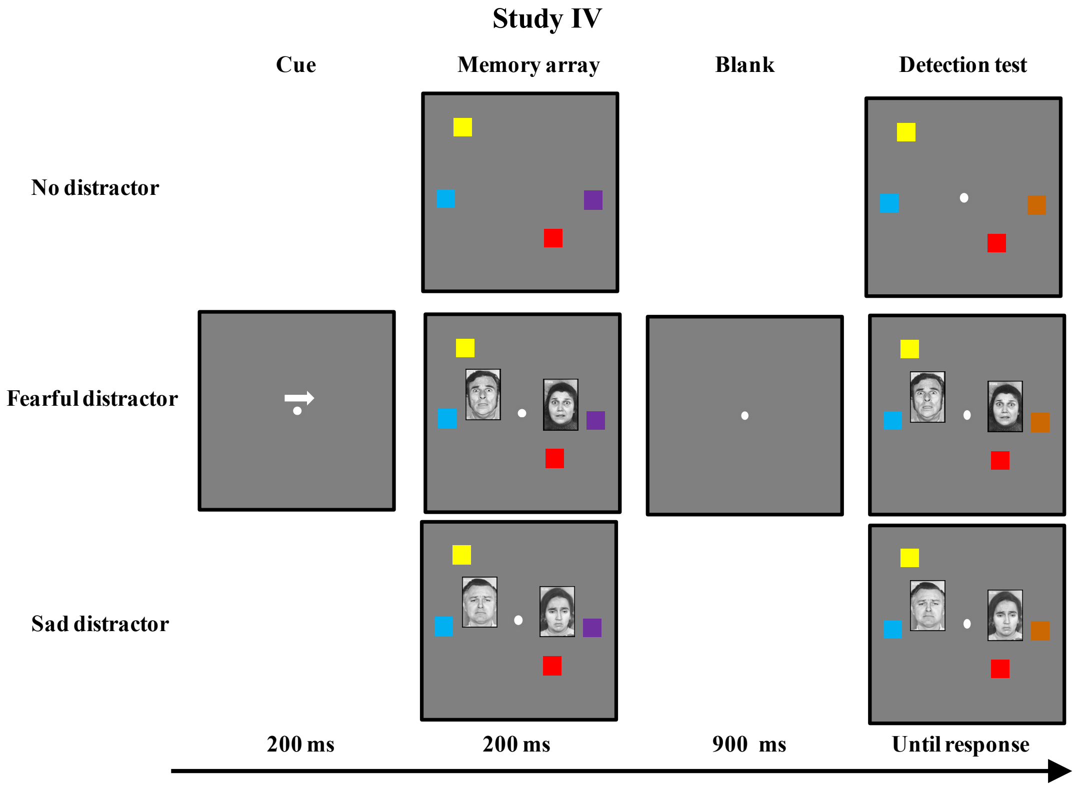

FIGURE 5 The trial structure of Experiment 7 in **Study IV**. Three memory type conditions (no distractor condition, fearful distractor condition, and sad distractor condition) are illustrated. Here, only trials with identity changes are shown, but there were also trials without a change. The figure is modified from Ye, Xu, Li, et al. (2020).

The Chinese Facial Affective Picture System (Gong et al., 2011) was used in **Study III** and the Pictures of Facial Affect (Ekman, 1976) was used in **Study IV**. These picture databases have been employed in several previous studies. The face pictures in the databases have been systematically evaluated and standardized (Ekman, 1976; Gong et al., 2011). I chose these picture databases to make the presented studies easier to compare with previous studies using the same databases.

In order to investigate the effect of individuals' VWM capacity on the experimental results, participants were asked to perform an additional VWM capacity measurement to measure their VWM capacity in **Study I**, **Study III**, and **Study IV**. Since the purpose of **Study II** was not related to VWM capacity, VWM measurements were not recorded in **Study II**. The VWM capacity of the participants was measured by asking them to remember the colors of six squares in a color change detection task. The trial structures of the color change task are depicted in Figure 6. In each trial, the memory array appeared after a fixation. The memory array consisted of six brightly colored squares drawn at random locations surrounding the fixation. Participants were instructed to remember the colors of the squares across a blank delay period. During the test, a test array containing one test color was presented. Participants needed to indicate whether the test color was the same as the one in that specific location in the memory array.

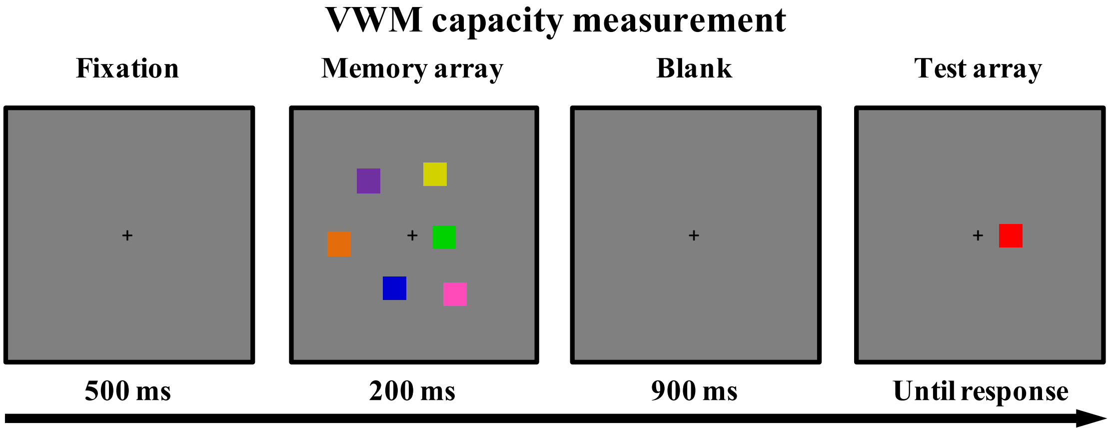

FIGURE 6 The trial structure of the VWM capacity measurement. Here, only a trial with a change in the colored squares is demonstrated, but there were also trials without a change. The figure is modified from Ye et al. (2018).

2.3 Analysis of behavioral data

In **Study I**, the general voluntary trade-off was calculated as the behavioral indicator. In **Study II**, memory precision (VWM precision index) and memory rate (VWM number index) were calculated as the behavioral indicators. In **Study III** and **Study IV**, the accuracy was calculated as the behavioral indicator. In addition, for **Study I**, **Study III**, and **Study IV**, the VWM capacity of each participant was calculated through VWM capacity measurements.

2.3.1 Memory rate, memory precision, and trade-off index

In the recall tasks of **Study I** (Experiments 1 and 2) and **Study II** (Experiments 3, 4, and 5), the distributions of recall error (calculated by subtracting the recalled item value from the target item value) in each condition were fit using the mixture model proposed by Zhang and Luck (2008). The data analysis was performed using the MemToolbox (Suchow et al., 2013). The model allowed for estimation of the memory rate in VWM (P) and the memory precision of the

VWM representations (SD^{-1}). The P value indicates the probability of correctly recalling the target item from VWM. The SD value is the circular SD of the von Mises distribution of recalling the target item. Thus, the SD value is inversely related to the precision of the VWM representations. Using the P and SD values, I quantified the memory rate and memory precision of **Study I** and **Study II**. In addition, I also used the swap model to fit the data of all experiments (Bays et al., 2009). I generally observed highly consistent results no matter which fitting model was used. In **Study I** and **Study II**, lower AICs were found using the mixture model compared to the swap model. This suggested that the mixture model has better goodness-of-fit to the data than the swap model. Thus, I only report the results of the mixture model below. More information about results of the swap model can be found in the individual publications and supplemental materials attached at the end of the book. The data were fitted with the mixture mode to independently measure the G (guess rate) and SD (circular standard deviation of von Mises distribution, inversely related to the precision of the representations) of the representations stored in VWM. The mixture model allowed us to estimate the correct memory rate (P) that the target item was correctly recalled from VWM as $1 - G$. Data analysis was performed using the MemToolbox (Suchow et al., 2013). The mixture mode was fitted to the data of each participant under both the high-precision and low-precision conditions. Since precision is inversely related to variance, I used the SD value (inversely related to the precision) as the VWM precision index and the P value (i.e., 1 – G) as the VWM number index.

In **Study I** (Experiments 1 and 2), I calculated a trade-off index based on the memory rate (P) and memory precision indices (SD) of each participant under the high-precision and low-precision conditions. By merging the voluntary trade-off magnitude in the memory rate and memory precision parameters (assuming equal weighting), a general voluntary trade-off (GT) could be defined as follows:

$$\mathrm{GT} = \frac{\mathrm{P}(low) - \mathrm{P}(high)}{\mathrm{P}(low)} + \frac{\mathrm{SD}(low) - \mathrm{SD}(high)}{\mathrm{SD}(low)}$$

In the literature, P and SD are typically analyzed separately. To capture the trade-off between the two variables, the novel "general voluntary trade-off (GT)" has been proposed here to combine both variables to capture the extent to which participants can voluntarily increase P and decrease SD according to the task demand. In the equation above, P(*low*) and P(*high*) refer to the memory rate parameter (P) under the low- and high-precision conditions. Similarly, SD(*low*) and SD(*high*) refer to the memory precision parameter (SD) under the low- and high-precision conditions. The GT value is, thus, the extent to which participants can voluntarily trade-off according to the task requirements (high or low precision).

2.3.2 VWM capacity

In **Study I** (Experiments 1 and 2), **Study III** (Experiment 6), and **Study IV** (Experiment 7), the VWM capacity (*K*) of each participant was calculated based on their hit rate (ratio of correctly identified changes) and false alarm rate (ratio of incorrect responses when no change was present). Based on the standard formula proposed by Cowan (2001), for each participant *K* = *Set size* × (*Hit rate - false alarm rate*). The memory array size was set to six in the VWM capacity measurement task in all experiments. In the presented studies, Cowan's *K* was used instead of other working memory tests (e.g., span tasks) to quantify the VWM capacity of the participants. This is not because I consider Cowan's *K* to be the best way to quantify VWM capacity, but because Cowan's *K* has been extensively used in previous studies with a similar experimental paradigm (Fukuda & Vogel, 2009; Fukuda et al., 2015; Owens et al., 2012; Vogel et al., 2005). The same approach enabled me to compare and discuss the present findings with the previous studies. In addition, I am aware that only the discrete resource models suggest a fixed item limit of VWM capacity. I used Cowan's *K* in my studies only to quantify the VWM performance of participants in the same way as in previous studies (Fukuda & Vogel, 2009; Fukuda et al., 2015; Owens et al., 2012; Vogel et al., 2005), but it does not mean that I have preferred discrete resource or continuous resource theories. That is, if a participant's *K* value is 2, I would think that the participant can maintain two items almost perfectly, but I would not conclude he/she has a fixed upper capacity limit of two items.

2.4 Electrophysiological recordings and analyses

2.4.1 Recording and preprocessing of the data

In **Study III** (Experiment 6) and **Study IV** (Experiment 7), the EEG data were recorded with a multiple channel sensor net (64 channels for Experiment 6 and 128 channels for Experiment 7), using Brain Vision Recorder software (Brain Products GmbH, Munich, Germany) amplified with Brain Vision QuickAmp. For Experiment 6, the EEG signals were low-pass filtered online (50 Hz) and digitized at a sampling rate of 500 Hz. For Experiment 7, the EEG and EOG signals were band-pass filtered online (0.1–250 Hz) and digitized at a sampling rate of 1 000 Hz. Offline, the data were preprocessed using the BrainVision Analyzer 2.1 (Brain Products GmbH, Munich, Germany). The average of the left and right mastoids (Experiment 6) and an average reference (Experiment 7) were applied. EEG and EOG signals were filtered with a low-end cut-off of 0.1 Hz and a high-end cut-off of 17 Hz (with a 24 dB/octave roll-off).

2.4.2 ERP data analysis

In **Study III** (Experiment 6), EEG was averaged offline over a 1 600 ms epoch, including a 200 ms pre-stimulus baseline, with epochs time-locked to memory array onset. In **Study IV** (Experiment 7), the EEG was averaged offline over a 1 300 ms epoch, including a 200 ms pre-stimulus baseline, with epochs time-locked to the memory array onset. Segments with eye-related artifacts and excessively large amplitude values (more than ±80 μV) were excluded from the analysis. Because the use of standard preprocessing tools (e.g., independent component analysis, ICA) to clean the eye-movement artifacts can cause underestimation of CDA components, eye movement was left uncorrected. Previous CDA studies have also abstained from using these methods to correct eye-movement artifacts (Adam et al., 2018; Feldmann-Wustefeld & Vogel, 2019; Feldmann-Wustefeld et al., 2018; Vogel & Machizawa, 2004; Vogel et al., 2005). Participants with rejection rates of more than 30% (10 participants in **Study III** and 12 participants in **Study IV**) were excluded from further analyses. The ratio of excluded participants in my studies (24% in **Study III** and 25% in **Study IV**) was similar to previous studies using CDA (36% in Sessa et al., 2011; 29% in Stout et al., 2013; respectively).

For each condition, mean contralateral and ipsilateral activity in the ERP was calculated for each participant with parietal–occipital electrodes based on previous studies (He et al., 2015; McCollough et al., 2007; Shen et al., 2013). The CDA amplitude was determined as the mean lateralized amplitude (determined by subtracting the ipsilateral activity from the contralateral activity). The time window was chosen based on previous reports (e.g., 500–1000 ms after the onset of memory array Luria et al., 2016; Vogel & Machizawa, 2004; Vogel et al., 2005) and confirmed by visual inspection of the grand-averaged data.

A visual inspection of the waveforms suggested that an N2pc component was elicited in **Study IV**. Thus, I also analyzed the N2pc component in **Study IV**. The N2pc is characterized by a more negative value of the attended stimulus recorded by the contralateral electrodes than the negative value recorded when the attended stimulus is ipsilateral. It is typically observed within 180–320 ms after the onset of the stimulus (Eimer, 1996; Hopf et al., 2000; Liu et al., 2016; Luck & Hillyard, 1994a, 1994b; Zhao et al., 2011). N2pc has been used widely to investigate the deployment of attention (Liu et al., 2016; Luck & Hillyard, 1994a, 1994b; Zhao et al., 2011). It is widely accepted that the N2pc is a metric for deployment of covert spatial visual attention (e.g. Kiss et al., 2008) or the onset of attentional engagement (e.g. Zivony et al., 2018).

The preprocessing and calculation of N2pc amplitude was similar to CDA amplitude. The N2pc was measured for each condition as the difference in mean amplitude between the ipsilateral and contralateral waveforms recorded at the analyzed electrodes PO7/PO8 (Eimer, 1996; Hopf et al., 2000; Liu et al., 2016; Luck & Hillyard, 1994a, 1994b; Zhao et al., 2011) 230–330 ms after the onset of the memory array.

2.5 Statistical analyses

In all studies, statistical analyses were carried out with SPSS software (version 24.0 IBM Inc, Armonk, NY). A significance threshold of $p < 0.05$ was used for all tests and comparisons. Repeated measures ANOVAs were conducted for each study. Follow-up two-tailed paired *t*-tests were used for the within-subjects effects and follow-up two-tailed independent samples *t*-tests were used for the between-subjects effects. In each study, I had a hypothesis for each analysis; therefore, there was no need for corrections for multiple comparisons. In addition, Bayes factors analysis was conducted for each *t*-test.

In each experiment (Experiments 1 and 2) of **Study I**, participants were divided into different capacity groups by the median split of their VWM capacity (*K*). P and SD were calculated separately for each precision condition (high-precision vs. low-precision; within-subjects factor) and VWM capacity group (high capacity vs. low capacity; between-subjects factor) and forwarded to an ANOVA (analysis of variance) for repeated measures. To follow the interaction effects found in the ANOVAs, I applied *t*-tests to compare the P value and SD value under different precision conditions (high-precision and low-precision) in both groups. In addition, the Pearson correlation coefficient was calculated to investigate the relationship between *K* and the general voluntary trade-off (GT).

In Experiment 3 and Experiment 4 of **Study II**, the P value and SD value were calculated separately for different emotional state conditions (negative emotional state vs. neutral emotional state). A *t*-test was applied to compare the P values and SD values under the different emotional state conditions. In Experiment 5 of **Study II**, the P value and SD value were calculated separately for each emotional state condition (negative emotional state vs. neutral emotional state; within-subjects factor) and each presentation time (short vs. long; within-subjects factor) then submitted to a repeated measures ANOVA. To follow the interaction effects found in the ANOVAs, I applied *t*-tests to compare the P value and SD value under the different emotional state conditions (negative and neutral emotional state) under both presentation times, respectively.

In **Study III** (Experiment 6), participants were divided into different capacity groups by the median split of their *K* value. Accuracy and CDA amplitude were calculated separately for each memory condition (1Nt vs. 1Nt1Nd vs. 1Nt1Ad vs. 1Nt1Hd vs. 2Nt vs. 1Nt1At vs. 1Nt1Ht; within-subjects factor) and VWM capacity group (high capacity vs. low capacity; between-subjects factor) then submitted to repeated measures ANOVAs. To follow the interaction effects found in the ANOVAs, I applied *t*-tests to compare CDA amplitude under neutral-related conditions (1Nt vs. 1Nt1Nd vs. 2Nt), angry-related conditions (1Nt vs. 1Nt1Ad vs. 1Nt1At), and happy-related conditions (1Nt vs. 1Nt1Hd vs. 1Nt1Ht) in high- and low-capacity groups, respectively.

In **Study IV** (Experiment 7), I utilized *t*-tests to compare the VWM capacity (*K*) between the dysphoric group and the control group. In addition, Pearson correlation coefficients were calculated to investigate the relationship between VWM capacity (*K*) and BDI-II scores. More importantly, accuracy, N2pc amplitude, and CDA amplitude were calculated separately for each memory condition (no distractor vs. fearful distractor vs. sad distractor; within-subjects factor) and participant group (dysphoric vs. control; between-subjects factor) then submitted to repeated measures ANOVAs. To follow the interaction effects found in the ANOVAs, I performed *t*-tests to compare the ERP amplitude under different memory conditions in both groups, separately.

3 SUMMARY OF RESULTS

3.1 Study I: Impact of VWM capacity on the ability to voluntarily trade off between VWM precision and number

By examining the correlation between VWM capacity and voluntary trade-off ability, **Study I** investigated whether the voluntary trade-off ability between the VWM number and precision varies according to VWM capacity. The voluntary trade-off ability was studied under different presentation time of memory array.

In Experiment 1, the ANOVA showed that, for both the VWM precision (SD) and VWM number indices (P), there was a significant main effect of the precision condition (low precision vs. high precision) and a significant interaction effect between precision condition and the VWM capacity group (low VWM capacity vs. high VWM capacity). However, no significant main effect of capacity group was found. Follow-up pairwise comparisons showed that for the high VWM capacity group, the SD value was lower under the high-precision condition than under the low-precision condition, while the P value was lower under the high-precision condition than under the low-precision condition. For the group with low VWM capacity, there were no differences in the P or SD values between the high- and low-precision conditions. Thus, when the presentation time was long (500 ms), VWM precision was higher in the high VWM capacity group under the high-precision condition than under the low-precision condition, while the memory rate under the high-precision condition was lower than under the low-precision condition. In contrast, for the low VWM capacity group, there were no differences in VWM precision or VWM number under either high- or low-precision conditions. These correlation results showed that VWM capacity and the general voluntary trade-off were positively correlated. Participants with low VWM capacity showed lower general trade-off magnitude, while those with high VWM capacity exhibited a much higher general trade-off magnitude (Figure 7a). These results suggested that VWM capacity did affect the voluntary trade-off when presentation time was long.

In Experiment 2, the ANOVA showed that for both the VWM precision (SD) and VWM number values (P), there were no significant main effects of the precision condition (low precision vs. high precision), no significant main effect of the VWM capacity group (low VWM capacity vs. high VWM capacity), and no significant interaction effect between precision condition and the VWM capacity group. In other words, for both the high and low VWM capacity groups, when the presentation time was short (200 ms), participants maintained the same number of VWM representations with the same precision under both the high- and low-precision conditions. No significant correlation was found between VWM capacity and general voluntary trade-off (Figure 7b). These results suggest that VWM capacity did not affect the voluntary trade-off when the presentation time was short.

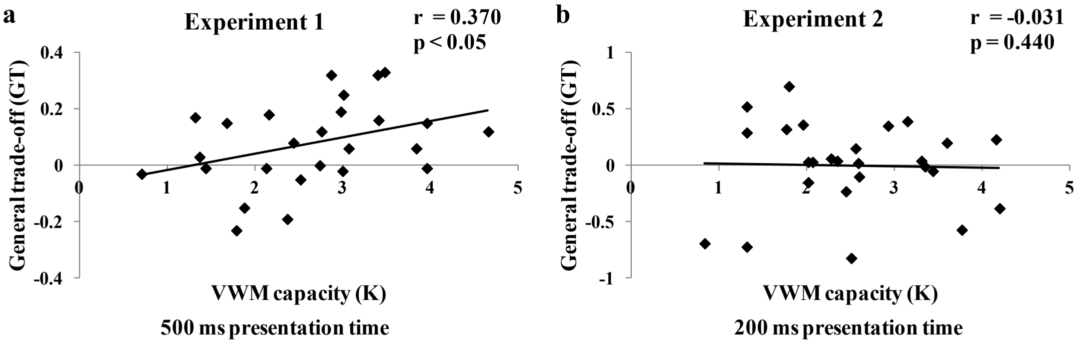

FIGURE 7 Correlation between VWM capacity (K) and general trade-off (GT) in (a) Experiment 1 and (b) Experiment 2. The figure is modified from Ye et al. (2019).

It is worth noting that, especially in Experiment 2, the general trade-off of many participants was negative or close to zero. These data suggest for some participants, memory precision could be higher under the low-precision condition than under the high-precision condition. This reflects that there could be great individual differences in the trade-off ability between individuals, especially when the participants fail to voluntarily trade off the VWM precision and VWM number. In summary, the results demonstrate that a positive correlation between VWM capacity and trade-off ability can only be found when the presentation time of the memory array is long.

3.2 Study II: Impact of a negative emotional state on the trade-off between VWM precision and number

Study II investigated whether a negative emotional state influences the trade-off between VWM precision and number. The VWM precision and memory rate were measured in neutral and negative emotional states with different memory array presentation times.

In Experiment 3, the results showed that for both VWM precision (SD) and VWM number indices (P), there were no significant differences in P and SD values between negative and neutral emotional state conditions. That is, when the presentation time was short (200 ms), participants maintained the same number of VWM representations with the same VWM precision under both negative and neutral emotional state conditions (Figure 8a–b). These results suggest that a negative emotional state did not affect the trade-off when the presentation time was short.

In Experiment 4, VWM precision (SD) under the neutral emotional state condition was significantly higher than under the negative emotional state condition. The VWM number (P) under the neutral emotional state condition was higher than that of the negative state condition. Thus, when the presentation time was long (500 ms), VWM precision was higher under the negative emotional state condition than under the neutral emotional state condition (Figure 8c), while the memory rate under the negative emotional state condition was lower than that of the neutral emotional state condition (see Figure 8d). These results suggest that negative emotional states affected trade-off when the presentation time was long.

In Experiment 5, the ANOVA results showed no significant interaction effects between emotional state (negative emotional state vs. neutral emotional state) and presentation time (200 ms vs. 500 ms) under both VWM precision (SD) and VWM number indices (P). Based on the P and SD values, there was no significant difference between the neutral emotional and negative emotional state conditions when the presentation time was 200 ms. When the presentation time was 500 ms, the SD value in the neutral emotional state condition was higher than that of the negative emotional state, while the P value under the neutral emotional state condition was higher than that of the negative emotional state. In other words, when the presentation time was short, there was no significant difference in VWM precision and memory rate between the neutral emotional and negative emotional state conditions. However, when the presentation time was long, VWM precision was significantly higher under the negative emotional state condition than under the neutral emotional state condition and the memory rate was significantly lower under the negative emotional state condition than under the neutral emotional state condition (see Figure 8e–f). The results in Experiment 5 were consistent with those of Experiments 3 and 4.

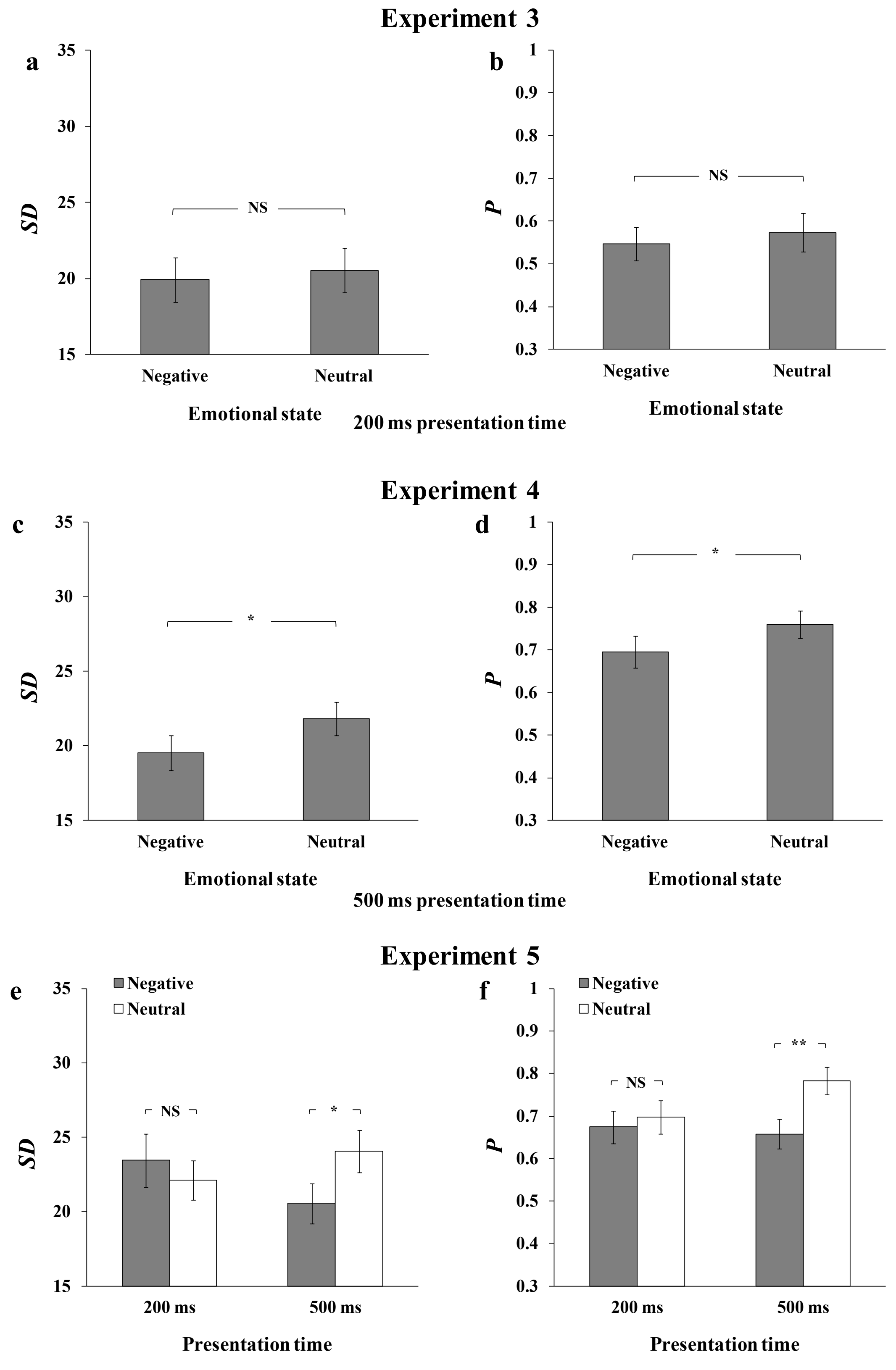

FIGURE 8 The results of (a–b) Experiment 3, (c–d) Experiment 4, and (e–f) Experiment 5. The (a, c, and e) VWM precision (SD) and (b, d, and f) memory rate parameters (P) are plotted separately for the neutral and negative conditions. Error bars represent the standard error of the mean. NS = non-significant, i.e., $p > 0.05$; ** = $p < 0.01$. The figure is modified from Long et al. (2020).

In summary, the results demonstrate that a negative emotional state did not affect the trade-off between VWM precision and VWM number when the presentation time of the memory array was short. However, when the presentation time of the memory array was long, participants increased their VWM precision while reducing their VWM number in the negative emotional state.

3.3 Study III: Impact of VWM capacity on the filtering of different expression distractors

By comparing behavioral performance and brain responses in adults with high and low VWM capacity, **Study III** (Experiment 6) investigated the relationship between VWM capacity and the filtering of expression (neutral, angry, and happy) distractors in a VWM task. The behavioral results for accuracy showed significant main effects of condition (1Nt vs. 1Nt1Nd vs. 1Nt1Ad vs. 1Nt1Hd vs. 2Nt vs. 1Nt1At vs. 1Nt1Ht) and the VWM capacity group (high VWM capacity vs. low VWM capacity), but no significant interaction between conditions by group (Figure 9). The accuracy in the high VWM capacity group was higher than that of the low VWM capacity group. Compared to the two target conditions (2Nt, 1Nt1At, and 1Nt1Ht), the accuracy was higher under the conditions in which participants only needed to memorize one target (1Nt, 1Nt1Nd, 1Nt1Ad, and 1Nt1Hd).

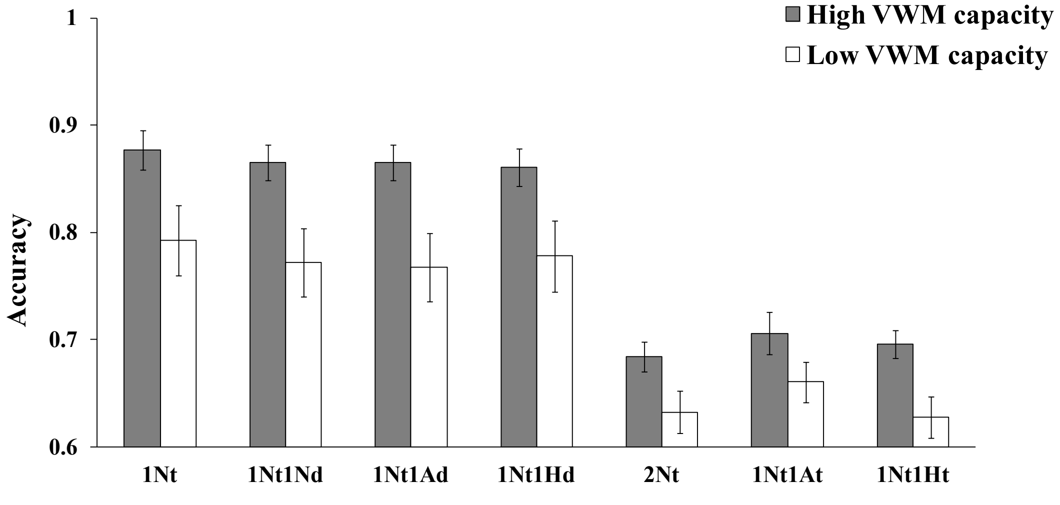

FIGURE 9 Accuracy results of Experiment 7 in **Study III**. The accuracy in the high VWM capacity group and low VWM capacity group is shown separately under each condition (1Nt: one neutral target face condition; 1Nt1Nd: one neutral target face and one neutral distractor face condition; 2Nt: two neutral target faces condition; 1Nt1Ad: one neutral target face and one angry distractor face condition; 1Nt1At: one neutral target face and one angry target face condition; 1Nt1Hd: one neutral target face and one happy distractor face condition; 1Nt1Ht: one neutral target face and one happy target face condition). Mean values with error bars show the standard error of the mean.

Using CDA, the filtering ability of different distractors (neutral, angry, and happy faces) in VWM was investigated in the dysphoric and control groups. The ANOVA revealed a significant main effect of condition and a significant interaction effect between condition and VWM capacity group, but no significant main effect of VWM capacity group was found.

The follow-up pairwise comparisons showed that, for the neutral-related conditions (1Nt, 1Nt1Nd, 2Nt) in the high VWM capacity group, the CDA amplitude under the 2Nt condition was larger than under both the 1Nt and 1Nt1Nd conditions, but there was no difference between the 1Nt and 1Nt1Nd conditions. In the low VWM capacity group, the CDA amplitudes under both the 1Nt1Nd and 2Nt conditions were larger than under the 1Nt condition, but there was no difference between the 2Nt and 1Nt1Nd conditions (Figure 10a and Figure 11a). These results suggest that the number of stored faces under the neutral distractor condition was no different from that of the one-target condition for the high VWM capacity group, while for the low VWM capacity group, the number of stored faces under the neutral distractor condition was no different from that of the two target condition. Therefore, the high VWM capacity group could filter out the neutral face distractor from VWM; whereas the low VWM capacity group could not.

For the angry-related conditions (1Nt, 1Nt1Ad, 1Nt1At) in the high VWM capacity group, the CDA amplitude under the 1Nt1At condition was larger than of both 1Nt conditions, but there was no difference between the 1Nt and 1Nt1Ad conditions. In the low VWM capacity group, the CDA amplitude under the 1Nt1At condition was significantly larger than under the 1Nt condition, but there was no different between the 1Nt1At and 1Nt1Ad conditions. The CDA amplitude was not significantly different between 1Nt1Ad and 1Nt conditions (Figure 10b and Figure 11b). These results show that the number of stored faces under the angry distractor condition was no different from that of the one-target condition for the high VWM capacity group, while for the low VWM capacity group, the number of stored faces under the angry distractor condition was no different from that of the two target condition. Therefore, the high VWM capacity group could filter out the angry face distractor from VWM, while the low VWM capacity group could not.

For the happy-related conditions (1Nt, 1Nt1Hd, 1Nt1At) in the high VWM capacity group, the CDA amplitude under the 1Nt1Ht condition was larger than under both the 1Nt and 1Nt1Hd conditions, but there was no difference between the 1Nt and 1Nt1Hd conditions. Similar to the high VWM capacity group, in the low VWM capacity group, the CDA amplitude under the 1Nt1Ht condition was significantly larger than under both the 1Nt and 1Nt1Hd conditions but was not different between the 1Nt and 1Nt1Hd conditions (Figure 10c and Figure 11c). These results suggest, for both the high and low VWM capacity groups, the number of stored faces under the happy distractor condition was no different from that of the one-target condition. Therefore, both high and low VWM capacity groups could filter out the happy face distractor from VWM.

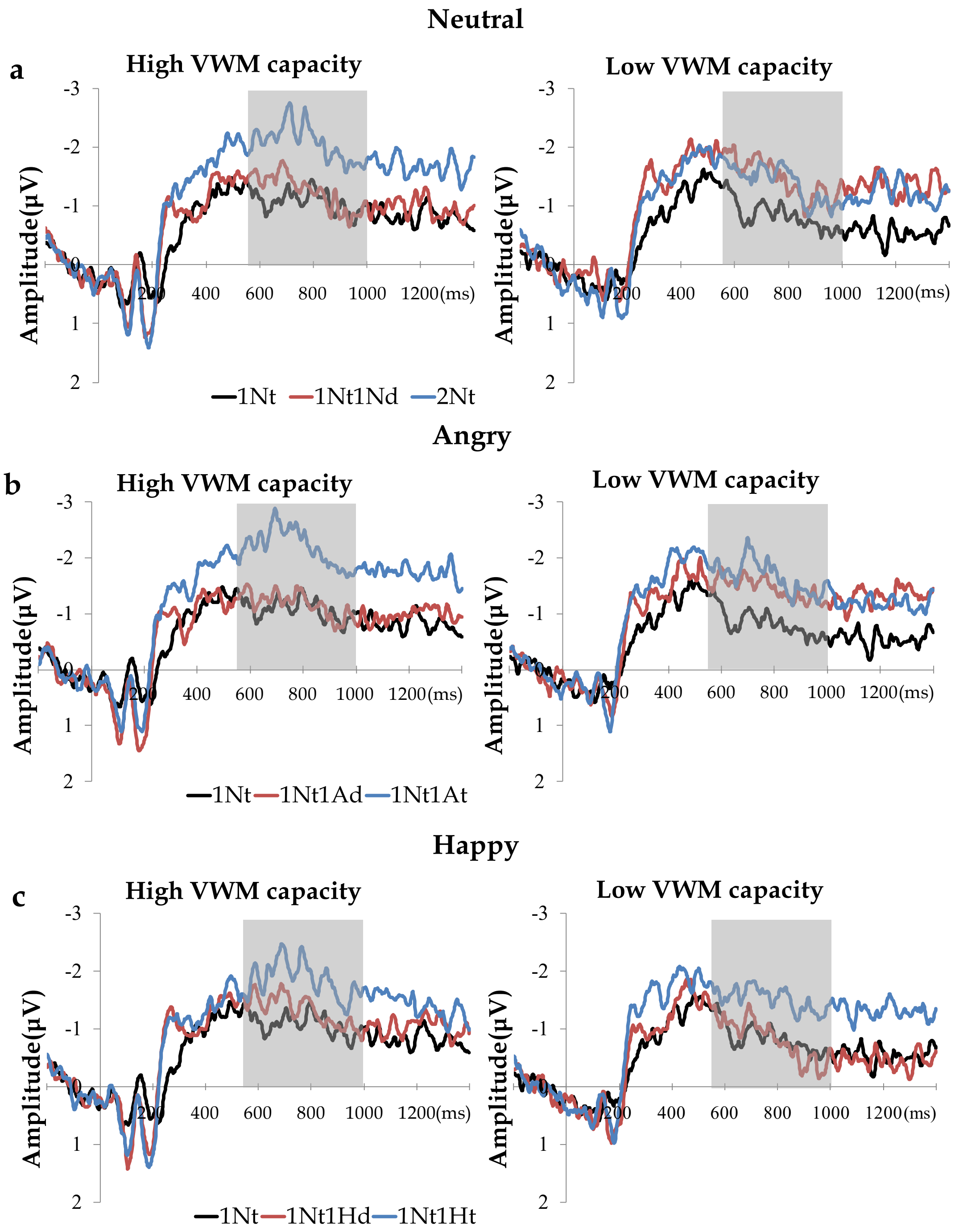

FIGURE 10 Grand-averaged ERP waveforms of Experiment 6 in **Study III**. (a) Grand-averaged ERP waveforms under neutral-related conditions (1Nt, 1Nt1Nd, and 2Nt) for the high (left) and low (right) VWM capacity groups. (b) Grand-averaged ERP waveforms under angry-related conditions (1Nt, 1Nt1Ad, and 1Nt1At) for the high (left) and low (right) VWM capacity groups. (d) Grand-averaged ERP waveforms under angry-related conditions (1Nt, 1Nt1Hd, and 1Nt1Ht) for the high (left) and low (right) VWM capacity groups. Gray areas indicate the time windows used to calculate the mean amplitude values for the CDA. 1Nt: one neutral target face condition; 1Nt1Nd: one neutral target face and one neutral distractor face condition; 2Nt: two neutral target faces condition; 1Nt1Ad: one neutral target face and one angry distractor face condition; 1Nt1At: one neutral target face and one angry target face condition; 1Nt1Hd: one neutral target face and one happy distractor face condition; 1Nt1Ht: one neutral target face and one happy target face condition.

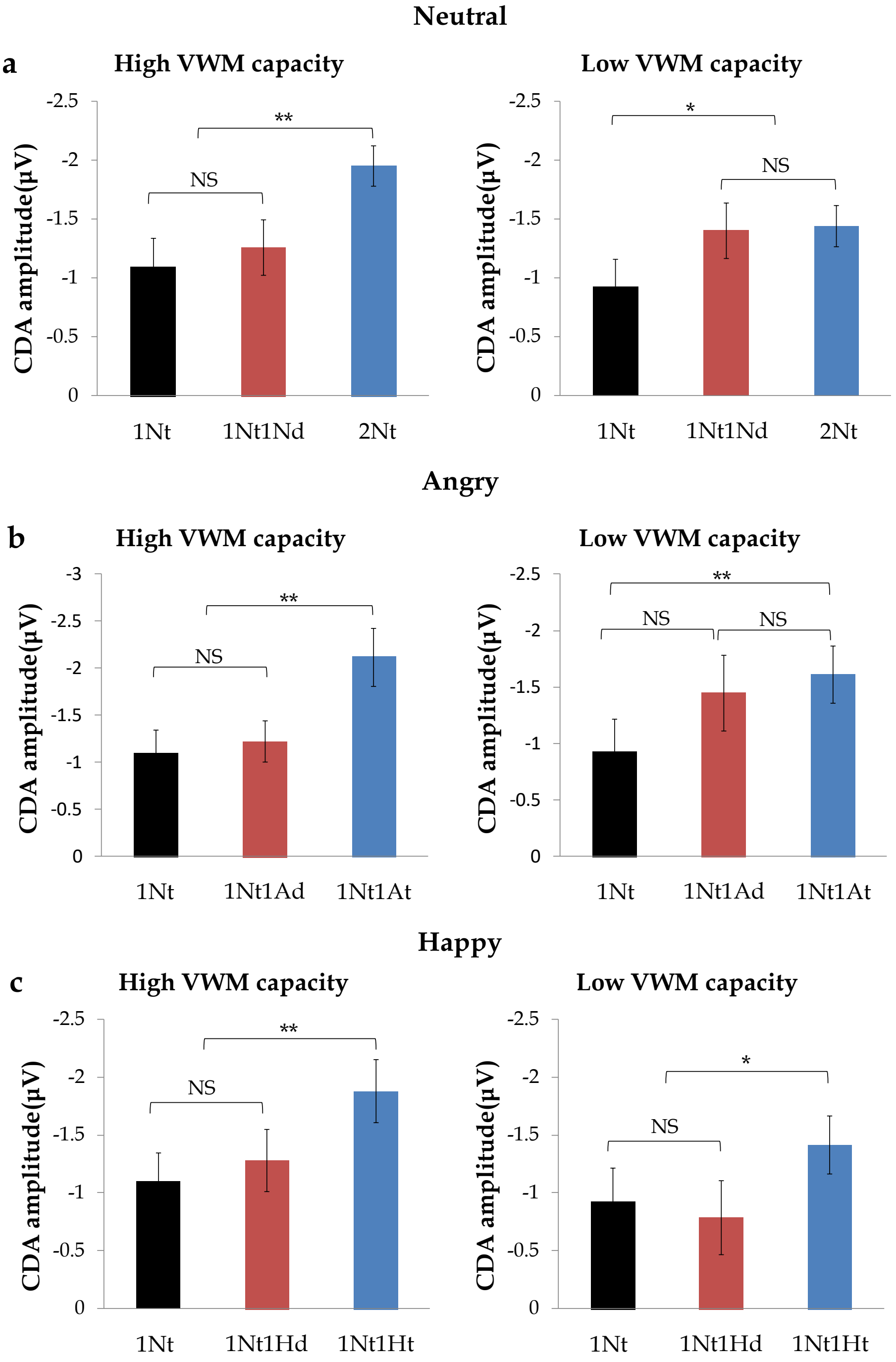

FIGURE 11 CDA amplitude results of Experiment 6 in **Study III**. The CDA amplitude results for the high VWM capacity participant (left) and low VWM capacity participant (right) groups under different conditions (1Nt: one neutral target face condition; 1Nt1Nd: one neutral target face and one neutral distractor face condition; 2Nt: two neutral target faces condition; 1Nt1Ad: one neutral target face and one angry distractor face condition; 1Nt1At: one neutral target face and one angry target face condition; 1Nt1Hd: one neutral target face and one happy distractor face condition; 1Nt1Ht: one neutral target face and one happy target face condition). CDA amplitudes in (a) neutral-related conditions (1Nt, 1Nt1Nd and 2Nt), (b) angry-related conditions (1Nt, 1Nt1Ad and 1Nt1At), and (c) happy-related conditions (1Nt, 1Nt1Hd and 1Nt1Ht). Bars show the mean amplitude values and their error bars depict the standard error of the mean. ** = $p < 0.01$; * = $p < 0.05$; NS = non-significant (i.e., $p > 0.05$).

In conclusion, the results from **Study III** demonstrate that high VWM capacity participants could filter neutral, angry, and happy face distractors. However, while the low VWM capacity participants could filter happy face distractors successfully, they had difficulties in filtering out both the angry and neutral face distractors.

3.4 Study IV: Impact of depressive symptoms on the filtering of negative face distractors

By comparing behavioral performance and brain responses in dysphoric and control adults, **Study IV** (Experiment 7) investigated the relationship between depressive symptoms and the filtering of negative face distractors in the VWM task. No significant difference in VWM capacity was found between the dysphoric and control groups. Similarly, there was no correlation between VWM capacity and BDI-II scores. The ANOVA for accuracy showed a significant main effect of condition (no distractor vs. fearful distractor vs. sad distractor), but neither a main effect of participant group (dysphoric vs. control) nor an interaction effect of condition and participant group. Under all conditions, there were no significant differences in accuracy between the dysphoric and control groups. For all participants, accuracy under the no distractor condition was higher than that of the fearful distractor and sad distractor conditions.

In addition, the ANOVA results for N2pc amplitude showed a significant main effect of condition. However, neither a significant main effect of group nor an interaction effect of condition by group was observed (Figure 12). A follow-up pairwise comparison showed that for all participants, the N2pc amplitude under the sad distractor condition was significantly larger than that of the fearful distractor condition and no distractor condition. There was no significant difference in N2pc amplitude between the fearful distractor condition and no distractor condition. The data imply that sad faces attract the attention of both control and dysphoric participants.

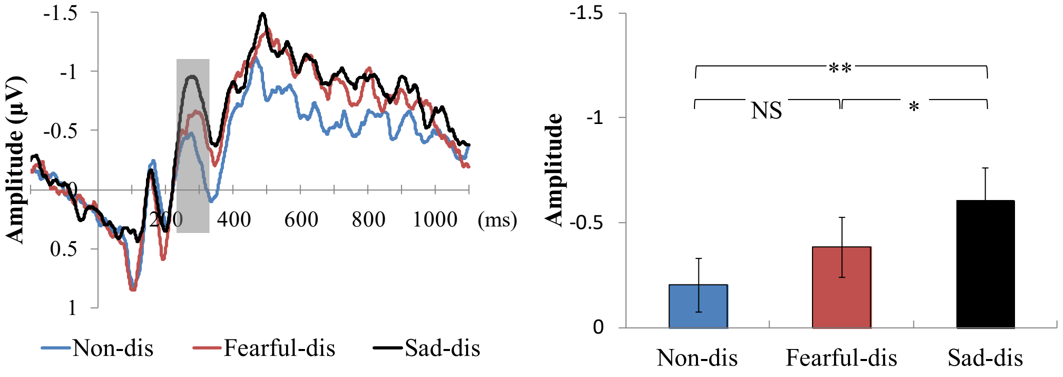

FIGURE 12 N2pc results of Experiment 7 in **Study IV**. Grand-averaged ERP waveforms (left). The waveforms time-locked to the onset of the memory array (y-axis at $t = 0$) under different conditions for all participants. The X-axis shows the time from the onset of the memory arrays in milliseconds. Gray areas indicate the time windows used to calculate the mean amplitude values for the N2pc. The results of the N2pc amplitude (right) for all participants under the conditions are listed separately. Bars show mean amplitude values and their error bars depict standard error of the mean. ** = $p < 0.01$; * = $p < 0.05$; NS = non-significant, i.e. $p > 0.05$. Non-dis = no distractor condition, Fearful-dis = fearful distractor condition, Sad-dis = sad distractor condition.

Using CDA, the filtering ability of negative expression (fearful face and sad face) distractors in VWM was investigated in the dysphoric and control groups. The ANOVA results for CDA amplitude revealed a significant main effect of condition and a significant interaction effect between condition and participant group, but no significant main effect of participant group. The follow-up pairwise comparisons showed, in the dysphoric group, there was no difference in CDA amplitude between the no distractor, fearful distractor, and sad distractor conditions (Figure 13a and 13c). These results suggest, in the fearful and sad distractor conditions, dysphoric participants stored as much visual information as they did in the no distractor condition. Thus, the dysphoric group could filter out both fearful and sad face distractors from VWM. In the control group, the CDA amplitude was larger under the fearful distractor condition than under the no distractor condition. There was no difference in CDA amplitude between the no distractor and sad distractor conditions or between the sad distractor and fearful distractor conditions (Figure 13b and 13c). The control participants stored more information under the fearful distractor condition than under the no distractor condition.

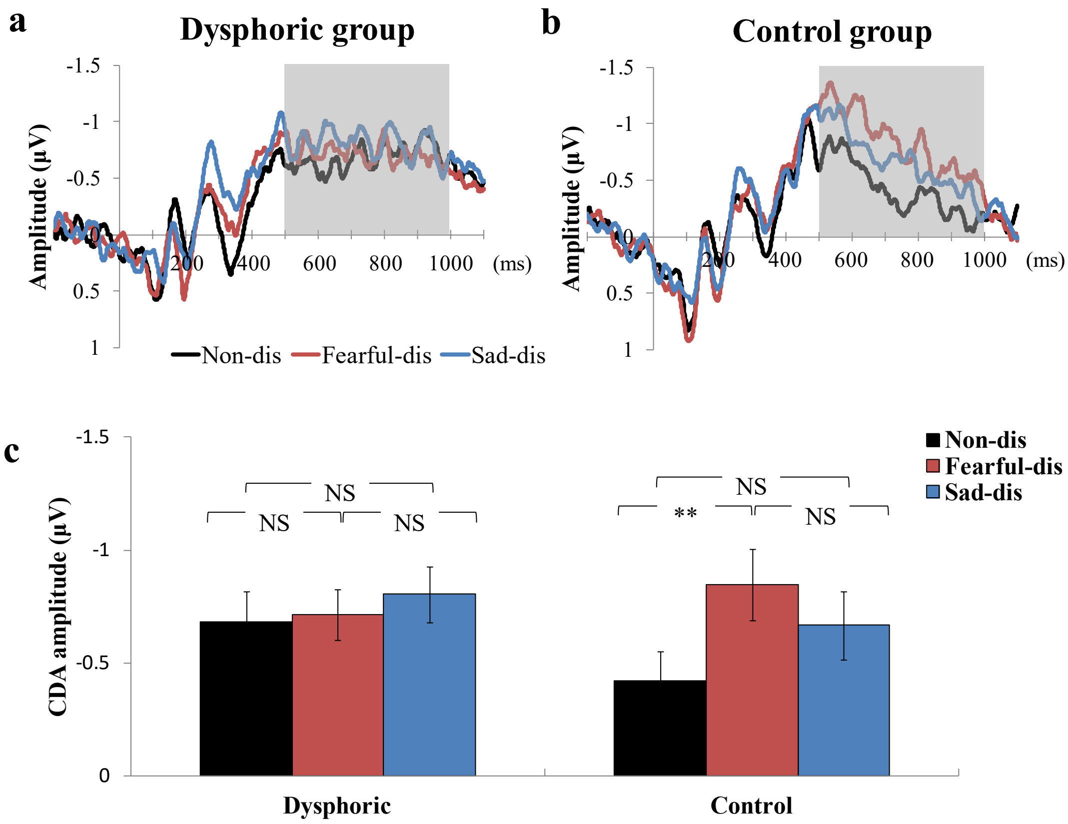

FIGURE 13 CDA results of Experiment 7 in **Study IV**. Grand-averaged ERP waveforms under different conditions (Non-dis: no distractor condition; Fearful-dis: fearful distractor condition; Sad-dis: sad distractor condition) for the (a) dysphoric group and (b) control group. Gray areas indicate the time windows used to calculate the mean amplitude values for the CDA. (c) The results of the CDA amplitude for the dysphoric (left) and control (right) groups under the conditions are listed separately. Bars show mean amplitude values and their error bars depict the standard error of the mean. ** = $p < 0.01$; NS = non-significant, i.e., $p > 0.05$.

Overall, the results indicate that dysphoric participants could filter out both sad and fearful face distractors. In contrast, control participants failed to filter out fearful face distractors but could filter sad face distractors efficiently.

4 DISCUSSION

The focus of my work was to explore the factors that affect the allocation of VWM resources. For this purpose, the trade-off between VWM precision and number and distractor filtering were investigated. To summarize the results, in the behavioral experiments of **Study I** and **Study II**, I used a recall task to explore the effects of VWM capacity and negative emotional state on the trade-off between VWM precision and VWM number under different memory array presentation times. In the ERP experiments of **Study III** and **Study IV**, using CDA components, I used a lateralized change detection task with face distractors to explore the influence of emotional type of face distractor, VWM capacity, and depressive symptoms on distractor filtering ability in VWM. In **Study I**, when the memory array presentation time was long, I found that participants with high VWM capacity were able to voluntarily adjust the trade-off between VWM precision and number according to different precision requirements. Low VWM capacity participants failed to adjust trade-off. In addition, the participants' VWM capacity was positively correlated with voluntary trade-off ability when most participants had enough consolidation time to trade off the VWM number and VWM precision. In contrast, when the presentation time was short, I found that most participants could not voluntarily trade off the VWM number and VWM precision. In **Study II**, when the memory array presentation time was short, I determined a negative emotional state did not affect the trade-off between VWM precision and number. In contrast, when the presentation time was long, a negative emotional state reduced the VWM number and increased VWM precision. In **Study III,** I found the high VWM capacity group was able to filter out neutral, angry, and happy face distractors, similarly. In contrast, the low VWM capacity group could filter out happy face distractors efficiently but were unable to filter either neutral or angry face distractors. In **Study IV**, I found that the control group unnecessarily stored fearful face distractors in VWM but were able to filter sad faces, while the dysphoric group could filter both fearful and sad face distractors efficiently.

4.1 VWM capacity modulates the trade-off ability when the stimulus presentation time is long

Study I aimed to investigate the effect of VWM capacity on the voluntary trade-off ability for VWM precision and number with different memory array presentation times. The results show, when the presentation time was short, participants could not voluntarily trade off VWM precision and number. However, when the presentation time was long enough, participants could voluntarily allocate resources and their VWM capacity was positively related to their trade-off ability. These results are consistent with the predictions of the two-phase VWM resource allocation model (Ye, 2018; Ye et al., 2017), indicating that there are two different phases in VWM consolidation depending on the length of consolidation time.

When participants could trade off between VWM precision and number, their VWM capacity was positively correlated to their voluntary trade-off ability. This result supports that there is a positive correlation between individuals' VWM resource allocation ability and their VWM capacity. This result could also explain previous studies using the VWM task with distractors, which suggested a positive correlation between VWM capacity and distractor filtering ability (Fukuda & Vogel, 2009; Vogel et al., 2005). However, as mentioned in the Introduction, the resource allocation process that was utilized in the studies on attentional filtering was not identical to the process that I used in **Study I**. The interaction between VWM and selective attention has been widely investigated in previous studies and the mental process underlying distractor filtering is primarily caused by selective attention (Griffin & Nobre, 2003; Landman et al., 2003; Lu et al., 2017; Soto et al., 2008; Ye et al., 2016). Chun et al. (2011) classified selective attention as external and internal attention. External attention is related to selection and control of external sensory information (e.g., filtering ability of the task-irrelevant visual distractors); meanwhile, internal attention refers to the selection, control, and maintenance of information generated within the brain (e.g., trade-off ability between VWM precision and VWM number). Therefore, **Study I** provides a necessary complement to the interaction between VWM and research on attention.

Most of the previous studies that supported the voluntary trade-off effect between VWM precision and VWM number used the orientation as their stimulus (Fougnie et al., 2016; Gao et al., 2011; Machizawa et al., 2012; Murray et al., 2012; Ye et al., 2017). However, studies using color materials usually failed to find evidence to support a voluntary trade-off (Bocincova et al., 2017; Ye et al., 2014; Zhang & Luck, 2011). Thus, the stimulus types (orientation vs. color) might be a factor in determining patterns in the results. A previous study suggests that orientation is a boundary feature, and the main characteristic of the color stimulus is its surface feature (Fougnie et al., 2016). As a result, there may be different underlying consolidation mechanisms for direction and color. For example, a series of previous studies showed that color materials and orientation materials result in different VWM consolidation processes (Becker et al., 2013; Hao et al., 2018; Liu & Becker, 2013; Mance et al., 2012; Miller et al., 2014). However, the results of **Study I** showed that participants could voluntarily trade off between VWM precision and number even with the color materials, thus rejecting the hypothesis that stimulus type determined the voluntary trade-off. According to the results of **Study I**, previous studies may have failed to find evidence to support a voluntary trade-off due to the short presentation time (Bocincova et al., 2017; Ye et al., 2014; Zhang & Luck, 2011). Therefore, although the study that proposed the two-phase model used orientation materials as stimuli (Ye et al., 2017), the results of **Study I** reveal that the two-phase model is also applicable to color materials.

In addition, the change detection tasks in Experiment 1 and Experiment 2 instructed participants to aim for either high-precision or low-precision (but with an increased number of items remembered). I am aware that the change detection task and recall task may test some common processes of VWM (Schurgin et al., 2020), but the focus of my investigation was not the relationship between these tasks in absolute performance (i.e., the relationship between VWM capacity and the offset in the recall task). For the change detection task, my interest was in the capacity, while in the recall task, my interest was in the performance difference following different sets of task instructions: high precision but few items vs. low precision but more items. The performance from these two precision levels allows me to calculate the extent of trade-off between precision and memory rate. The relationship between VWM capacity (obtained in the change detection task) and trade-off (obtained in the recall task) was the goal of **Study I**. One way to illustrate such a relationship is to partition the entire sample of participants into two groups based on memory capacity then compare the trade-off indices of these two capacity groups. It emerges that trade-off was evident for the high capacity group only and for long presentation time only. Moreover, the relationship in absolute performance between the change detection task and the recall task could not explain the null result found under the short presentation time condition. Therefore, the academic value of Study I goes beyond simply exploring the relationship between the participants' performance in the change detection and recall tasks.

4.2 Negative emotional state modulates the trade-off between VWM precision and number when the stimulus presentation time is long

Study II aimed to investigate the effect of a negative emotional state on VWM precision and number with different presentation times of the same memory array. The results suggest that a negative emotional state did not affect VWM precision and number when the stimuli presentation time was short. However, when the presentation time was long enough, participants could improve VWM precision while reducing the VWM number in a negative emotional state

Based on the predictions of the two-phase model (Ye et al., 2017), the resource allocation in the process of VWM consolidation can be divided into early and late phases. The results of **Study II** show that the negative emotional state mainly influenced the late phase of resource allocation during memory consolidation. These results are consistent with those of Li et al. (2010). Using a change detection task, they investigated the effect of a negative emotional state on visuospatial and verbal working memory. Compared to a neutral emotional state, they found that a negative emotional state resulted in worse memory performance. Furthermore, their ERP results showed that the main difference between the two emotional states (negative vs. neutral) occurred in the maintenance phase of VWM after early consolidation, implying that the effect of a negative emotional state on VWM is distinctly phase-specific.

In research related to emotions and VWM, in addition to the effect of emotional states on VWM, some previous studies have also directly addressed the influence of emotional content on VWM (Jackson et al., 2014; Jackson et al., 2009; Linden et al., 2011; Sessa et al., 2011), similar to my **Study III**. These studies widely showed a memory advantage with emotional stimuli, especially negative emotional stimuli (e.g., angry faces) compared to neutral stimuli, which suggests that emotional stimuli can enhance VWM processing (Jackson et al., 2014; Jackson et al., 2009). However, given that negative emotional stimuli have different sensory attributes from neutral stimuli, studies on the effect of emotional content on VWM are unavoidably influenced by attentional bias (Maljkovic & Martini, 2005). However, there was no such confusion in **Study II** because the memory content was always simple neutral items when the emotional states were manipulated. These settings ensured that the effect of the emotional state on VWM mainly resulted from the late phase rather than to the early phase of resource allocation in VWM consolidation.

It is natural to ask whether different emotional states really modulate VWM resource allocation or just manipulate the generic task strategies of participants under different emotional conditions (e.g., strategically trading quantity for quality only in the negative emotional condition). By mixing different emotional conditions in each block, Experiment 2 in Xie and Zhang (2016)'s study provided evidence that the effect of emotional modulation was not due to the difference in generic task strategy. Moreover, in my Experiment 5, I mixed different presentation time conditions in each emotional block. I found that there were differences in trade-off patterns under different presentation time conditions in the same emotional block. More importantly, participants who used different generic task strategies under different emotional conditions had no obvious benefit. The difference in generic task strategy under different emotional blocks seems difficult to explain the results of Experiment 5. It is possible that the trade-off of precision and capacity was based on automatic resource allocation (i.e., cognitive process bias). When individuals are able to reallocate the VWM resource (at the late phase of VWM resource allocation), they may have an involuntary bias to trade quantity for quality in a negative emotional state. This involuntary bias for quality might have evolved from the need to maintain more detailed information to deal with potential dangers that often arise in negative situations. Previous studies could support this idea. For example, Sessa et al. (2011)'s study has shown that the VWM precision of a fearful face is higher than that of a neutral face.

A recent study has shown that in the recall task, the response data may show categorical response bias or decision criterion (Hardman et al., 2017). Thus, it is possible that the difference in trade-off patterns between VWM precision and number in different emotional states was due to the effect of the negative emotional state on categorical response bias or decision criterion. That is, the emotional state modulates the tendency to make a response based on categorical information or decision criterion. However, this possibility does not explain why the negative emotional state could not affect the trade-off under the short presentation time (200 ms) condition. Therefore, categorical response bias and decision criterion might not be the main reason differences between different emotional state conditions are caused in **Study II**.

4.3 High VWM capacity participants can filter all distractors, while low VWM capacity participants can only filter happy distractors

Study III investigated the effect of VWM capacity on the filtering of different expression distractors in VWM. It was found that VWM capacity modulated the filtering of neutral, angry, and happy face distractors. High VWM capacity participants were able to filter all face distractors. However, while low VWM capacity participants were able to filter happy face distractors, they had difficulties in filtering angry and neutral face distractors.

The results related to filtering neural faces are in line with previous studies investigating the filtering of simple neutral objects (Vogel et al., 2005). In both **Study III** and the study of Vogel et al. (2005), participants with high VWM capacity could filter out task-irrelevant objects, while low VWM capacity participants maintained task-irrelevant information in VWM. This indicates that the mechanism of filtering simple neutral objects (e.g., orientations or colors) could be extended to complex neutral objects (e.g., faces).

Previous studies suggest, compared to neutral faces, fearful distractors are much harder to filter (Stout et al., 2013). In the study of Stout et al. (2013), a similar procedure to the one applied in **Study III** was used to investigate filtering efficiencies of fearful and neutral face distractors. They found that the fearful distractor condition showed a higher CDA amplitude compared to the one-target condition. However, there was no difference between the one-target condition and the neutral distractor condition in terms of CDA amplitude. Interestingly, the results of **Study III** showed that high VWM capacity participants were able to filter out another kind of threat-related distractor (angry faces). The discrepancy between **Study III** and Stout et al. (2013)'s study may be due to the different neurological mechanisms recruited by fearful and angry faces, which convey different social meanings and can activate the brain differently (Fitzgerald et al., 2006; Whalen et al., 1998). Furthermore, although angry faces can effectively capture attention (Fox et al., 2000; Hansen & Hansen, 1988; Pinkham et al., 2010), participants with high VWM capacity appear to have strong resistance to this attention capture; thus, they successfully filter out angry face distractors. However, participants with low VWM capacity cannot efficiently filter angry faces. This result is consistent with a previous study showing that, compared to participants with low VWM, high VWM capacity participants were better able to resist attentional capture from distractor stimuli (Fukuda & Vogel, 2009).

Interestingly, both groups of participants in **Study III** could filter happy face distractors effectively, but the low VWM capacity group was not able to filter neutral and angry distractors. Therefore, it seems that low VWM capacity individuals have different filtering efficiencies for different expressions. One recent study provided insight. Tay and Yang (2017) applied a directed forgetting paradigm and found that angry faces showed more resistance to intentional forgetting compared to happy faces. This result suggests that angry faces were more likely to be retained in memory compared to happy faces, even in situations in which participants took great effort to forget them. Therefore, it can be assumed that individuals with low VWM capacity may have a similar ability to consolidate happy, angry, and neutral face distractors, but during VWM maintenance, they may quickly forget happy distractor stimuli. Further, Tay and Yang (2017) interpreted their results to indicate that attentional and extra cognitive resources were dedicated to angry faces. This explanation is also well suited to explain the results of **Study III**. The involuntary attentional bias for potentially threatening faces may have evolved as a result of the need to maintain enough information to cope with the dangers of the external environment (e.g., potentially threatening persons). In **Study III**, the results show that low VWM capacity individuals had difficulties filtering both angry and neutral faces. One possibility is that neutral faces serve as potentially threatening expressions in attention capture, while happy faces are more likely to be interpreted as non-threatening information (Nummenmaa & Calvo, 2015).

Therefore, **Study III** demonstrates that individuals with different VWM capacities have different filtering abilities stemming from different expression distractors. Low VWM capacity seems to make filtering potentially threatening information (neutral and angry faces) particularly difficult.

4.4 Dysphoric participants can filter fearful and sad distractors, while control participants cannot filter fearful distractors

Study IV aimed to investigate the effect of depressive symptoms on the filtering of fearful and sad face distractors in VWM. Although the N2pc results showed that there was no significant difference in the level of attention given to the distractor between the control and dysphoric groups, it was found that depressive symptoms modulated distractor filtering. The results from the control participants showed that they could not effectively filter fearful faces. In contrast, sad faces were efficiently filtered. There was a clear group difference in fearful face filtering: the dysphoric group could filter both sad and fearful face distractors.

In the control group, CDA amplitude under the fearful distractor condition was larger than that of the no distractor condition. These results were well aligned with the unnecessary storage of fearful faces into VWM. In a study by Stout et al. (2013), both the target and distractor items that were used belonged to the same stimulus category (faces); thus, distinguishing targets and distractors in their study was probably more challenging than in my **Study IV**. The results of **Study IV** and Stout et al. (2013)'s study suggest that fearful faces are difficult for control participants to entirely filter from VWM, even when they are easy to differentiate from the targets.

Contrary to the results of fearful face filtering, there was no difference in CDA amplitude between the no distractor and sad distractor conditions or between the sad distractor and fearful distractor conditions. These results suggest that sad faces were not unnecessarily stored in VWM by the control group. Previous CDA studies have not applied sad face distractors, providing novelty to the study. Thus, this finding suggests that the control participants do not store all kinds of negative facial distractors in VWM; rather, they selectively store potentially dangerous signals (i.e., fearful face distractors) automatically, even if they are task-irrelevant. This finding is congruent with a large number of studies demonstrating that the processing of threat-related stimuli is prioritized in the human brain (LeDoux, 1996). Threatening faces are detected faster (Eimer & Holmes, 2002; Ohman et al., 2001; Schupp et al., 2004) and they elicit earlier attentional bias in the brain than the other facial expressions do (Bayle & Taylor, 2010; Luo et al., 2010; Smith et al., 2003; Stefanics et al., 2012).

For the dysphoric group, it can be expected that the negative attentional bias would lead to difficulty in suppressing attention to sad distractors (Allon & Luria, 2019) as well as unnecessary storage of the sad distractor. Indeed, the N2pc results in **Study IV** show that sad faces attract more attention in the dysphoric group—but the same result pattern was found in the control group. However, contrary to these expectations, the results of the dysphoric group showed no difference in CDA amplitude between the no distractor condition and the sad distractor condition. This implies that the filtering out of both the sad and fearful face distractors was effective in the dysphoric group. While there is a well-documented negative bias toward sad faces in individuals with depression (e.g., Armstrong & Olatunji, 2012; Gotlib & Joormann, 2010), the dysphoric group showed no difficulty in filtering the task-irrelevant sad faces. It is possible that sad faces attracted the attention of the dysphoric participants (supported by the N2pc results), but they did not store them in VWM. For example, a recent eye-tracking study showed that a guiding effect of task-irrelevant content on attention is involuntary only in the early stage of visual search and, after this stage, the task-irrelevant content can be strategically inhibited (Lu et al., 2017). Therefore, attentional bias toward sad faces does not necessarily lead to unnecessary memory storage of those faces. Another possibility is that exogenous attention capture by task-irrelevant sad faces was not evident in the present paradigm. A recent ERP study suggested that, when compared to positive faces, sad faces were more difficult to recognize and required more late attention and perceptual resource engagement in the VWM task (Liu et al., 2020).

In addition, a similar pattern in the control and dysphoric group could be expected in regard to the filtering of fearful faces, as there is no clear evidence of threat-related bias in dysphoria. However, I found no difference in CDA amplitude between the no distractor and fearful distractor conditions in the dysphoric group. Thus, the data cannot inform whether threat detection is somehow dysfunctional in depression (Armstrong & Olatunji, 2012). It is perhaps more probable that the efficient filtering of facial distractors in the dysphoric group can be explained by the decreased overall responsiveness to emotional stimuli in this sample (i.e. emotion context insensitivity, e.g., Rottenberg & Hindash, 2015), possibly resulting in less interest in human faces in the dysphoric group than in the control group. This could also explain why filtering was not only efficient for fearful faces but sad faces in the dysphoric group, also.

One possible confounding factor underlying the null result of the CDA amplitude between the conditions in the dysphoric group could be dysphoric individuals' poor memory. It may be that dysphoric participants' resources were depleted with two items (thus, not further increasing for distractors); whereas the control group sometimes encoded irrelevant faces because resources were left over. That is, remembering the colors of two objects could, in principle, reach dysphoric participants' maximum VWM capacity. In this case, it would be difficult to observe whether they have stored additional distractors into VWM by using CDA amplitude. However, the data of **Study IV** from the capacity measurement and behavioral accuracy did not support this assumption. Namely, I found no significant difference in VWM capacity and behavioral accuracy in the face filtering memory task between non-dysphoric participants and dysphoric participants (both *K*s > 2). The accuracy of both groups in the task was higher than 90%, which indicated that both control and dysphoric participants could memorize two color targets very well and have extra memory space to store distractors. That is, if the control participants have enough memory space to store additional distractors, the dysphoric participants should also have enough space to store more information.

4.5 General discussion

Through the investigation of individual trade-off ability and filtering ability, my studies explored the influence of different factors—stimulus presentation time in **Study I** and **Study II**; emotional state in **Study II**; facial expression of distractor in **Study III** and **Study IV**; VWM capacity in **Study I**, **Study II**, and **Study IV**; and depressive symptoms in **Study IV**—on resource allocation in VWM. Among these factors, stimulus presentation time and the facial expression of the distractor are stimulus-related factors, while emotional state, VWM capacity, and depressive symptoms are individual-related factors (state-related and trait-related). In addition to the factors discussed here, there are many other factors that may impact VWM resource allocation, including other stimulus-related factors: stimulus complexity (e.g., simple or complex, see Alvarez & Cavanagh, 2004), stimulus type (e.g., color or orientation, see Miller et al., 2014), stimulus presentation method (e.g., serially present or simultaneously present, see Miller et al., 2014); as well as other participant-related factors: age (e.g., young or old, see Shimi et al., 2014) and health status (e.g., healthy or sleepless, see Xie et al., 2019). Therefore, future research could further explore the impact of other factors on VWM.

In my studies, the VWM resource allocation mechanism is investigated by testing trade-off (**Study I** and **Study II**) and distractor filtering ability (**Study III** and **Study IV**). The trade-off ability mainly reflects the modulation of internal attention on VWM resources, while distractor filtering ability reflects the modulation of both external and internal attention on VWM resources. Therefore, my work will be beneficial to future research on the interaction between VWM and attention.

The investigation of VWM capacity is a crux of my work. The findings suggest that people with higher VWM capacity (those who can remember more items) tend to have better resource allocation ability (including trade-off ability and distractor filtering ability). Although the studies in this book cannot reveal the direct causal relationship between VWM capacity and resource allocation ability, it is reasonable to speculate that an effective VWM resource allocation mechanism enables individuals to store more representations in VWM at the same time. In the future, it is necessary to further investigate the causal relationship between VWM capacity and VWM resource allocation ability.

Another focus of my work was to investigate the effect of emotional information on VWM resource allocation. The findings suggest that negative emotional information has a special effect on the VWM process. This is mainly reflected in the fact that people will concentrate their VWM resources on a small number of items in a negative emotional state. It is also reflected in the fact that negative emotional stimuli can automatically attract attention, which makes it more difficult for individuals (especially low VWM capacity or non-dysphoric individuals) to filter negative emotional information out of VWM. This biased mechanism for negative emotional information may help people evade potential dangers found in the external environment.

Study I and **Study II** were designed based on the predictions of the two-phase model to verify the impact of VWM resource allocation (Ye, 2018; Ye et al., 2017). The results show that in the early phase of VWM consolidation, resource allocation is not affected by participant-related factors (e.g., emotional state, VWM capacity, allocation strategy). That is, resource allocation is an automatic process in the early phase. However, in the late phase of VWM consolidation, people can flexibly allocate resources according to the task. Thus, resource allocation is affected by participant-related factors. Since research on the two-phase model chiefly includes behavioral studies, it is necessary to further explore these two phases of resource allocation using EEG.

In addition, **Study I** implemented two levels of presentation time (500 ms and 200 ms) and found only a positive relation between VWM capacity and general trade-off capacity for the 500 ms stimulus. This pattern is consistent with the two-phase model when the early phase is likely longer than 200 ms (Ye, 2018; Ye et al., 2017). However, it could be that there is only one phase but the VWM precision varies continuously and merely appears categorical because two different presentation times were used. I named this possibility as the single-phase hypothesis. Indeed, my recent study found that participants allocated the resources gradually to each memory representation in the early VWM consolidation stage. (Ye, Liang, et al., 2020) I also found that after each representation received minimum resources for completing the early stage, participants could then allocate the rest of the resources to the consolidated representations to further improve memory precision. Because I only tested two time segments in **Study I** and **Study II**, the results of my studies did not provide enough resolution in the stimulus presentation time to prove or disprove the single phase hypothesis. Thus, the data in **Study I** and **Study II** alone cannot provide all the evidence to support that the two phases proposed by the two-phase model are qualitatively different and independent of each other. Future studies could be conducted to vary systematically the stimulus presentation time and if, for a given individual, there is a threshold for stimulus presentation time when the trade-off starts to emerge, I will have more direct evidence to support the two-phase model.

It should be pointed out that, although there are many studies fitting the mixture or swap model to investigate the trade-off between VWM precision and the VWM number (Bocincova et al., 2017; Fougnie et al., 2016; Ramaty & Luria, 2018; Ye et al., 2017; Zhang & Luck, 2011), all of them measured VWM precision and number separately. In **Study I**, I used GT as the metric to merge VWM precision and number to quantify the magnitude of voluntary trade-off. To the best of my knowledge, this is the first time that researchers have considered VWM precision and number together to quantify the magnitude of trade-off.

This combined setup (i.e., GT) in **Study I** is a new beginning for quantifying individuals' trade-off ability.

In **Study III** and **Study IV**, I focused on the filtering of expression distractors in the VWM task. To my knowledge, this is the first ERP evidence for distractor filtering employing happy faces, angry faces, and sad faces in the VWM task. Since I used the same picture databases as many previous studies without the added control of expression strength in the different stimuli, I could not separate the emotion factor and stimulus feature factor in these studies. For example, the sad faces contained quite modest changes in visual features compared to the other emotions. It is possible that stimulus features affect the present results. However, this conjecture does not explain why different patterns of results in different participant groups were found in my studies. If stimulus features, such non-emotional information, have an impact on my results, this effect should be observed in each participant group. Thus, the different patterns of results from different participant groups suggest that the results are more likely to be caused by the emotional information.

Although **Study III** and **Study IV** revealed the phenomenon of expression filtering, I could not find any existing theoretical model that could adequately explain my findings. However, in **Study IV**, I found that the pattern of the N2pc result was different from that of CDA, which indicates that previous attention-related theories could not explain the distractor filtering in VWM. Therefore, it is necessary to further explore this phenomenon of expression distractor filtering in the future.

In **Study IV**, I chose a presentation time of 200 ms for the memory array based on the color change detection task. Previous findings from dot-probe paradigms suggested that depressed individuals may have an abnormal inclination toward depression-relevant stimuli only if the stimuli are presented for a longer period of time (500–1000 ms, see Bradley et al., 1997; Gotlib et al., 2004). Future studies could investigate the effect of distractor presentation time on filtering ability in dysphoria/depression. Additional studies are needed to investigate whether attentional bias toward negative stimuli in depression can cause unnecessary storage of sad faces when the distractors are presented for a longer time or when participants have more severe (i.e., clinical) depression.

Previous studies have shown that dysphoric participants have lower VWM capacity than healthy participants (Owens et al., 2012). However, in **Study IV**, no significant difference in VWM capacity was found between the dysphoric and control groups. To investigate the reason for this, I compared the VWM capacity of the control group in **Study IV** ($K = 2.66 \pm 1.005$) with that of the control groups in the other studies (**Study I** and **Study III**, $K = 2.41 \pm 0.884$) and found that there were no significant differences in the VWM capacities of these healthy participants ($p = 0.289$). Interestingly, this implies that this dysphoric group may be just the high VWM capacity sample in the dysphoric population. In fact, this is certainly plausible, as participants were informed that **Study IV** was a memory-related experiment when they were recruited, so dysphoric individuals with low VWM capacity might have been more reluctant to participate in this study. However, this possibility could not be tested based on the current data. Future research could examine the filtering of emotional distractors by dysphoric participants with high or low VWM capacity.

It is worth noting that my studies in this book do not directly address the discrepancy between the two theories of VWM: discrete resource VWM models and continuous resource models. The most fundamental difference between the discrete resource and continuous resource theories is whether individuals can increase the number of items stored by decreasing representation precision when it is necessary to memorize more than four items (i.e., the proposed upper limit of VWM capacity according to discrete resource theory) (Bays, 2015; Bays & Husain, 2008; Luck & Vogel, 2013; Zhang & Luck, 2008). However, in my studies, participants never needed to memorize more than four items (the magic number, see Cowan, 2001). As I mentioned in the Introduction, when the number of items to be memorized does not exceed the upper limit of individual's VWM capacity, discrete resource theory and continuous resource theory have similar predictions for VWM performance. Thus, my studies could not test the two theories. More recently, some studies have found evidence to support the discrete resource models (Balaban et al., 2019), but the continuous resource models have received more support (Emrich et al., 2017; van den Berg et al., 2014; Veksler et al., 2017). I would like to point out that the results of my studies fit both the discrete resource and continuous resource theories. My studies should not be considered as evidence to test these theories. The investigation of the difference between the two theories is beyond the scope of the studies herein.

There are some limitations to the samples I chose in my studies. There was an imbalance in the gender of the participants, as 71.3% of the participants in the studies were females. It is possible that there is a general gender difference in emotional processing: one influential study suggests that females were more susceptible than males to negative stimuli (Li et al., 2008). Thus, the gender of the participants may have contributed to the studies related to emotion (**Study II**, **Study III**, and **Study IV**). Therefore, more research is needed before the findings of these studies can be generalized.

In conclusion, the studies presented in this book suggest that the resource allocation pattern changes with the stimulus presentation time. The trade-off between VWM precision and number is associated with the VWM capacity of individuals and their emotional state. In VWM, distractor filtering is modulated by the expression of the distractors, an individual's VWM capacity, and an individual's depressive symptoms. My findings suggest that stimulus presentation time, emotional state, the emotional information of the distractor, VWM capacity, and depressive symptoms are all factors that affect resource allocation in VWM. Based on these findings, future research could further examine the interaction between the VWM system and other cognitive mechanisms (e.g., attention control, emotion process), which could possibly develop methods for cognitive training and clinical purposes, as well.

YHTEENVETO (FINNISH SUMMARY)

Visuaalisen työmuistin resurssit: ärsykkeiden ja yksilön tilan ja piirteiden vaikutus

Visuaalinen työmuisti on systeemi, jota käytetään aktiivisesti ylläpitämään näköaistitietoa kognitiivisten tehtävien suorittamiseksi. Tehokas visuaalinen työmuisti mahdollistaa oleellisen tiedon valinnan visuaalisesta ympäristöstä, tallentamaan tiedon korkealla tarkkuudella ja suodattamaan epäoleellisen tiedon. Viime vuosina käyttäytymis- ja aivotutkimus on selvittänyt visuaalisen työmuistin mekanismeja. Kognitiivisten ja emotionaalisten tekijöiden vaikutusta visuaaliseen työmuistiin ei silti vielä tarkasti tunneta. Tämän väitöskirjatyön tarkoituksena oli tutkia, mitkä tekijät vaikuttavat visuaaliseen työmuistiin. Tämän selvittämiseksi manipuloin osatutkimuksissa sekä ärsykkeisiin (kuten ärsykkeen esittämisaika ja tunnepitoinen sisältö) että tutkittavien tilaan (tunnetila) liittyviä tekijöitä. Lisäksi tutkin yksilöllisen työmuistikapasiteetin ja masennusoireiden vaikutusta työmuistiin.

Ensimmäisessä osatutkimuksessa selvitin tutkittavien työmuistikapasiteetin yhteyttä heidän kykyynsä jakaa muistiresursseja käyttäen erilaisia ärsykkeen esittämisaikoja. Käytin käyttäytymisvasteita mittaamaan tutkittavien työmuistin kapasiteettia ja kykyä muistiresurssien kohdentamiseen. Sain selville, että kun ärsykkeen esitysaika oli pitkä (500 ms), työmuistikapasiteetti ja muistiresurssien kohdentaminen olivat yhteydessä toisiinsa: tutkittavat, joilla oli suurempi visuaalisen työmuistin kapasiteetti, oli myös parempi kyky jakaa muistiresursseja. Kun ärsykkeen esitysaika oli lyhyt (200 ms), vastaavaa yhteyttä ei löytynyt. Näin ollen oli riippuvaista tutkittavan visuaalisen työmuistin kapasiteetista, kuinka joustavasti he kykenivät kohdentamaan muistiresurssejaan, mutta tämä tulos havaittiin ainoastaan, kun muistiaineksen esittämisaika oli riittävän pitkä. Tulokset viittaavat siihen, että visuaalisessa työmuistiprosessissa on kaksi eri vaihetta riippuen ajasta, joka on käytettävissä muistiin tallentamiseen. Yksilön visuaalisen työmuistin kapasiteetti näytti vaikuttavan visuaalisen työmuistin kiinnittymisessä ainoastaan sen myöhempään vaiheeseen.

Toinen osatutkimus selvitti negatiivisen tunnetilan vaikutusta visuaalisen työmuistin laatuun ja työmuistiin tallennettujen edustuksien määrään eri ärsykkeen esitysajoilla. Käytin käyttäytymiskokeissa neutraaleja ja negatiivisia kuvia tuottamaan tutkittaville vastaavan tunnetilan. Sen jälkeen mittasin muistitiedon edustuksien määrää ja laatua kunkin tunnetilan aikana. Havaitsin, että kun ärsykkeen esitysaika oli lyhyt (200 ms), visuaalisen työmuistin tarkkuus ja edustuksien määrä eivät eronneet neutraalin ja negatiivisen tunnetilan aikana. Sen sijaan, kun esitysaika oli pitkä (500 ms), työmuistin tarkkuus oli parempi ja edustuksien määrä pienempi negatiivisen tunnetilan aikana verrattuna neutraaliin tunnetilaan. Nämä tulokset viittaavat siihen, että negatiivinen tunnetila vaikuttaa visuaalisen työmuistin laatuun ja edustuksien määrään ainoastaan, kun ärsykkeen esittämisaika on riittävän pitkä. On mahdollista, että negatiivisessa tunnetilassa ollessaan ihminen kykenee parantamaan visuaalisen työmuistin laatua vähentämällä työmuistissa olevien edustuksien määrää.

Kolmannessa osatutkimuksessa selvitin, onko visuaalisen työmuistin kapasiteetilla vaikutusta tunnepitoisten kasvojen suodattamiseen visuaalisen työmuistitehtävän aikana. Tässä tutkimuksessa tutkittavien tuli suodattaa visuaalisesta työmuistista pois tehtävän kannalta epäoleelliset iloiset, neutraalit ja vihaiset kasvokuvat pyrkiessään muistamaan kohdekasvot. Käytin aivojen sähköfysiologisia vasteita mittaamaan tallensivatko tutkittavat tarpeettomasti tunnepitoisia kasvokuvia työmuistiin. Havaitsin että tutkittavat, joilla oli suuri työmuistikapasiteetti, kykenivät suodattamaan epäoleelliset kasvoärsykkeet. Sen sijaan tutkittavat, joilla oli pieni muistikapasiteetti, tarpeettomasti tallensivat neutraaleja ja vihaisia kasvokuvia työmuistiin, vaikkakin iloisten kasvojen suodattaminen onnistui. Pieni työmuistikapasiteetti näyttää siis tekevän potentiaalisesti uhkaavien kasvojen suodattamisen erityisen vaikeaksi.

Neljäs osatutkimus selvitti vaikuttavatko masennusoireet negatiivisten kasvojen suodattamiseen työmuistista. Ryhmä tutkittavia, joilla oli masennusoireita, ja kontrolliryhmä osallistuivat samankaltaiseen tutkimukseen kuin kolmas osatutkimus. Tutkittavien tuli suodattaa pelokkaita ja surullisia kasvoja tehdessään työmuistitehtävää liittyen objektien väriin. Havaitsin että masennusryhmän tutkittavat eivät tarpeettomasti tallentaneet visuaalista informaatiota pelokkaista ja surullisista kasvoista. Sen sijaan kontrolliryhmä tallensi muistiinsa tehtävän kannalta tarpeettomasti informaatiota pelokkaista kasvoista. Tulokset osoittavat, että masennusoireet vaikuttavat negatiivisten kasvojen suodattamiseen työmuistitehtävän aikana, mutta tulos oli odottamaton, sillä suodattaminen oli tehokkaampaa masennusryhmässä kuin kontrolliryhmässä.

Kokonaisuutenaan tämän väitöskirjatutkimuksen tulokset viittaavat siihen, että visuaalinen työmuistiprosessi on riippuvainen ärsykkeen esittämisajasta. Lisäksi muistiresurssien kohdentamiskyky on yhteydessä työmuistikapasiteettiin ja yksilön tunnetila vaikuttaa siihen. Kyky suodattaa tunnepitoisia kasvoja on riippuvainen sekä kasvon ilmeestä, työmuistikapasiteetista että yksilön masennusoireista. Nämä löydökset osoittavat, että ärsykkeen esittämisaika ja sen tunnepitoisuus, yksilön työmuistikapasiteetti ja masennusoireet ovat tekijöitä, jotka vaikuttavat työmuistiresurssien kohdentamiseen. Näihin tuloksiin perustuen tulevaisuudessa voidaan tarkemmin tutkia visuaalisen työmuistin ja muiden tiedonkäsittelyn mekanismien vuorovaikutusta ja mahdollisesti kehittää myös menetelmiä kliiniseen työhön ja kognitiivisen harjoitteluun liittyen.

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ORIGINAL PAPERS

I

WORKING MEMORY CAPACITY AFFECTS TRADE-OFF BETWEEN QUALITY AND QUANTITY ONLY WHEN STIMULUS EXPOSURE DURATION IS SUFFICIENT: EVIDENCE FOR THE TWO-PHASE MODEL

by

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Working memory capacity affects trade-off between quality and quantity only when stimulus exposure duration is sufficient: Evidence for the two-phase model

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The relation between visual working memory (VWM) capacity and attention has attracted much interest. In this study, we investigated the correlation between the participants' VWM capacity and their ability to voluntarily trade off the precision and number of items remembered. The two-phase resource allocation model proposed by Ye *et al*. (2017) suggests that for a given set size, it takes a certain amount of consolidation time for an individual to control attention to adjust the VWM resources to trade off the precision and number. To verify whether trade-off ability varies across VWM capacity, we measured each individual's VWM capacity and then conducted a colour recall task to examine their trade-off ability. By manipulating the task requirement, participants were instructed to memorise either more colours in a low-precision way or fewer colours in a high-precision way. We conducted two experiments by adjusting stimulus duration to be longer than predicted critical value (Experiment 1) and duration shorter than predicted critical value (Experiment 2). While the results of Experiment 1 showed a positive correlation between the VWM capacity and trade-off ability, the results of Experiment 2 showed a lack of such correlation. These results are consistent with the prediction from the two-phase model.

Visual working memory (VWM) is a system to actively maintain visual information and provide the information for advanced cognitive processing[1]. This system provides a storage space as a buffer to integrate information into continuous visual experience. By maintaining the mental contents after the visual scene disappears, this system plays a role as a gatekeeper between perception and high-level cognition[2].

It is well known that VWM capacity develops in childhood, peaks in adulthood, and then declines with age[3,4]. Previous studies also found that VWM capacity differs substantially across different populations, and the VWM impairment is associated with a variety of cognitive disorders, such as Parkinson's disorder[5] and schizophrenia[6,7]. Moreover, there are reliable individual differences in VWM capacity even for healthy population[8]. Some individuals show VWM capacity of four items or above, whereas others show VWM capacity of two or less[9]. Besides, these individual differences are robustly correlated with many advanced cognitive functions such as fluid intelligence[10]. Therefore, understanding the relation between VWM capacity and other cognitive constructs is an essential topic in this field.

Many studies have investigated the relationship between individuals' VWM capacity and attention control ability[11–16]. A well-established consensus is that individuals with low VWM capacity are poor at exerting attention control over what is being consolidated and maintained in VWM. For example, evidence provided by Vogel, *et al.*[13] clearly illustrated this relationship. They identified a contralateral delay activity (CDA), an ERP component strongly modulated by the number of items in VWM during the maintenance phase and reaches an asymptote once VWM capacity is exhausted. They asked participants to memorise simple targets and ignore distractors.

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The CDA amplitude was used as an index of whether irrelevant distractors unnecessarily consumed VWM storage. The results suggested that participants with high VWM capacity were able to filter out the distractors, but low VWM capacity participants tended to fail to filter out distractors and involuntarily allocate VWM storage to them. By using a similar technique, a recent study also found that even when social stimuli such as emotional faces acted as distractors in a VWM task, high VWM capacity participants could still filter face distractors entirely, while participants with low VWM capacity automatically stored neutral and angry face distractors into VWM[14]. These studies have shown that low VWM capacity individuals could not help but orient their attention to distractors[11], and thus they ended up storing more distractors in their limited-capacity VWM than high VWM capacity individuals[13]. Therefore, the individual's VWM capacity is highly related to the attention efficiency for target selection (also see Cowan and Morey[17]). Although this individual difference approach successfully clarified the critical relationship between VWM capacity and attention control in the tasks with distractors[11,13,14,18], it is still unclear how attention control ability is affected by the VWM capacity in other tasks.

In tasks without distractors, the attention control can be studied in tasks requiring a voluntary trade-off ability in VWM resource allocation. Here, the trade-off ability for VWM precision and number refers to a situation in which individuals adjust the VWM resource allocation voluntarily, while the lack of trade-off ability refers to a situation where individuals can only allocate VWM resource involuntarily. So far in the literature, there have been many studies on whether individuals could voluntarily trade off the VWM precision and number[19–28], but the conclusion is still debated.

Zhang and Luck[23] investigated whether participants could voluntarily trade off the VWM precision and number when they have enough incentives. In their Experiment 3, they asked participants to memorise four colours and then recall one of the colours. After the response in each trial, feedback would be presented to inform them about their performance. They gave participants different incentives to trade off the VWM precision and number by manipulating the rules of the feedback. In the low-precision condition, participants could get some rewards even when recalling colours with low-precision. On the contrary, in the high-precision condition, only when they reported the colour with high precision, they would be told that they were correct and received more monetary rewards. However, Zhang and Luck[23] did not find any evidence to support the voluntary trade-off ability in individuals with their experimental setting. Similarly, Murray, *et al.*[19] asked participants to memorise stimuli in a way that emphasised precision or number, and only observed the null effects. These results support that the resource could only be allocated in a stimulus-driven (involuntary) manner.

However, the phenomenon of voluntary trade-off has been reported in some other studies. In an ERP study, Gao, *et al.*[24] asked participants to memorise orientations of items with either low-precision or high-precision. Their results showed that, in low-precision condition, participants could retain three to four items in VWM, but in high-precision condition, participants could only retain two items in VWM. Similarly, Machizawa, *et al.*[20] found that participants could adjust the memory precision when the memory load was low (two items) according to different task requirements. These results suggest that people have a voluntary trade-off ability, and support that the resource could also be allocated in a goal-directed (voluntary) manner.

Recently, Ye, *et al.*[21] proposed a two-phase VWM resource allocation model that can explain these two different patterns of results[19,20,23,24]. In their experiments, they used an orientation recall task. Similar to Experiment 3 and 4b in Zhang and Luck's[23] study, by manipulating the feedback following each trial, Ye, *et al.*[21] asked participants to memorise different numbers of orientations in different precision blocks. The novel aspect of the study is that stimulus exposure duration and set size were systematically manipulated. They found no effect of precision requirement with a high set size and short exposure duration (stored four items with 200 ms exposure duration). However, when the set size was low (stored two items with 200 ms exposure duration) or the exposure duration was long (stored four items with 500 ms exposure duration), participants could trade off the VWM precision and number according to task requirements. These results were interpreted with the two-phase VWM resource allocation model. The model states that in the early phase the VWM resource could only be allocated in a stimulus-driven (involuntary) manner. However, the allocation could enter the late phase after the completion of the first phase. In the late phase, the allocation could be controlled flexibly according to task requirements in a goal-directed (voluntary) manner. In other words, individuals automatically allocate VWM resources in the early phase and create a low-precision representation for each item in the scope of attention. After the low-precision representations have been entirely created or the VWM resources have been completely allocated, the individual can reallocate VWM resources and create high-precision representations according to the requirements of the task. Therefore, for a given set size, it takes a certain amount of consolidation time for an individual to control attention to adjust resources to trade off the memory precision and number in the VWM task without distractors.

Table 1 summarises stimulus and result patterns found in ten published papers in the literature about the voluntary trade-off between VWM precision and number[19–28]. The table also reports whether these experiments support an individual's voluntary trade-off for VWM precision and number. In 23 out of 25 experiments reported, when the exposure duration per stimulus item equalled or exceeded 100 ms/item, trade-off between the VWM number with precision occurred, however, when the exposure duration per stimulus item was equal or smaller than 50 ms/item, trade-off between the VWM precision with number did not occur. We thus speculate that the different patterns of results in terms of the trade-off between VWM precision and number could be determined by a critical value of the ratio of duration/set size (a value between 50–100 ms/item). The two-phase VWM resource allocation model could explain such critical value influencing the trade-off.

It is reasonable to argue that the critical value of duration/set size affecting trade-off could be related to individual participants' VWM capacities. All ten studies described above examined the participants' performance at a population level (using the mean performance of the sample). An alternative way to identify the critical factor affecting the trade-off is to examine the relation between trade-off tendency and *individual*'s capacity. Although so far in the literature there have been many studies examining whether individuals could trade off the VWM

Study	Experiment	N	Task	Stimulus	Set size	Duration (ms)	Duration/set size (ms/item)	Trade off voluntarily?	Can the critical value hypothesis predict it?
Zhang and Luck[23]	Experiment 1a	13	Recall	Colour	4	200 ms	50 ms/item	No	Yes
	Experiment 1b	13	Recall	Colour	4	200 ms	50 ms/item	No	Yes
	Experiment 2	14	Recall	Colour	4	200 ms	50 ms/item	No	Yes
	Experiment 3	10	Recall	Colour	4	200 ms	50 ms/item	No	Yes
	Experiment 4	10	Recall	Colour	6	200 ms	33.3 ms/item	No	Yes
Gao *et al.*[24]		19	Change detection (CDA)	Orientation	2,4	500 ms	125, 250 ms/item	Yes	Yes
Murray *et al.*[19]	Experiment 1	12	Change detection	Orientation	4	200 ms	50 ms/item	No	Yes
	Experiment 2	20	Change detection	Orientation	4	200 ms	50 ms/item	No	Yes
	Experiment 3	20	Change detection	Orientation	4	200 ms	50 ms/item	No	Yes
	Experiment 4	20	Change detection	Orientation	4	200 ms	50 ms/item	No	Yes
Machizawa *et al.*[20]	Experiment 1	20	Change detection	Orientation	2 4	200 ms 200 ms	100 ms/item 50 ms/item	Yes No	Yes Yes
	Experiment 2	20	Change detection (CDA)	Orientation	2 4	200 ms 200 ms	100 ms/item 50 ms/item	Yes No	Yes Yes
Ye *et al.*[22]		14	Change detection (CDA)	Colour	2, 3, 4	100 ms	25–50 ms/item	No	Yes
He *et al.*[27]	Experiment 1	12	Change detection (CDA)	Colour	2, 4	200 ms	50–100 ms/item	No	Yes
	Experiment 2	21	Change detection (CDA)	Colour	2, 4	200 ms	50–100 ms/item	No	Yes
Fougnie *et al.*[26]	Experiment 1	18	Recall	Colour	5	1200 ms	240 ms/item	Yes	Yes
	Supplementary experiment	18	Recall	Colour	5	200 ms	40 ms/item	Yes	No
	Experiment 2	18	Recall	Colour	5	1200 ms	240 ms/item	Yes	Yes
Bocincova *et al.*[25]		60	Recall	Colour	2, 4	150 ms	37.5–75 ms/item	No	Yes
Ye *et al.*[21]	Experiment 1	47	Recall	Orientation	4	200 ms	50 ms/item	No	Yes
	Experiment 2	50	Recall	Orientation	2	200 ms	100 ms/item	Yes	Yes
	Experiment 3	47	Recall	Orientation	4	500 ms	125 ms/item	Yes	Yes
Ramaty and Luria[28]	Experiment 1	20	Recall	Colour	5	1200 ms	240 ms/item	Yes	Yes
	Experiment 2	20	Recall	Colour	5	300 ms	60 ms/item	No	Yes
	Experiment 3	20	Recall	Colour	5	1200 ms	240 ms/item	No	No

Table 1. A summary of the studies about the voluntary trade-off between VWM precision and number.

precision and number[19–28], surprisingly, the impact of individual's VWM capacity on the trade-off ability of VWM precision and number have not been carefully examined.

The current study takes a novel approach to examine the effect of individual VWM capacity on the underlying process in resource allocation. To be more comparable with Zhang and Luck[23], we conducted a similar colour recall task to examine participants' trade-off ability. In order to verify whether trade-off ability varies across VWM capacity, we first measured each individual's VWM capacity and then conducted the colour recall task to examine their trade-off ability. By using different feedback to manipulate task requirements, participants were asked to memorise colours in different precision conditions. We conducted two experiments using a ratio of duration/set size higher than the predicted critical value (Experiment 1) and a ratio lower than the predicted value (Experiment 2).

We anticipated that, at the population level, with a high ratio of duration/set size provided in Experiment 1, we would find that participants in the high VWM capacity group could trade off the precision and number according to task requirements, but participants in the low VWM capacity group could not. However, with a low ratio provided in Experiment 2, neither high VWM capacity participants nor low VWM capacity participants could trade off the precision and number. Moreover, at the individual level, with a high ratio of duration/set size provided in Experiment 1, we would see a relation between trade-off ability and VWM capacity, as for most participants, they would have completed the early phase and entered the late phase of the two-phase model in which allocation could be controlled voluntarily according to task requirements. In contrast, with a low ratio provided in Experiment 2, we would not see such a relation, as for most participants, the processing would still be in the early phase of the model in which VWM resource could be allocated only by an involuntary manner.

Experiment 1

Based on the study by Ye, *et al.*[21], when 500 ms exposure duration was used for four memory items, participants were able to trade off the VWM precision and number, we adopted this ratio of 125 ms/item in our Experiment 1.

Methods.

Participants. A total of 26 undergraduate students (21.19 ± 1.02 years old, age range 18–22 years; 21 females) were recruited from the participant pool at the Minnan Normal University of China. They reported normal or corrected-to-normal vision and no history of neurological problems. Participants gave informed

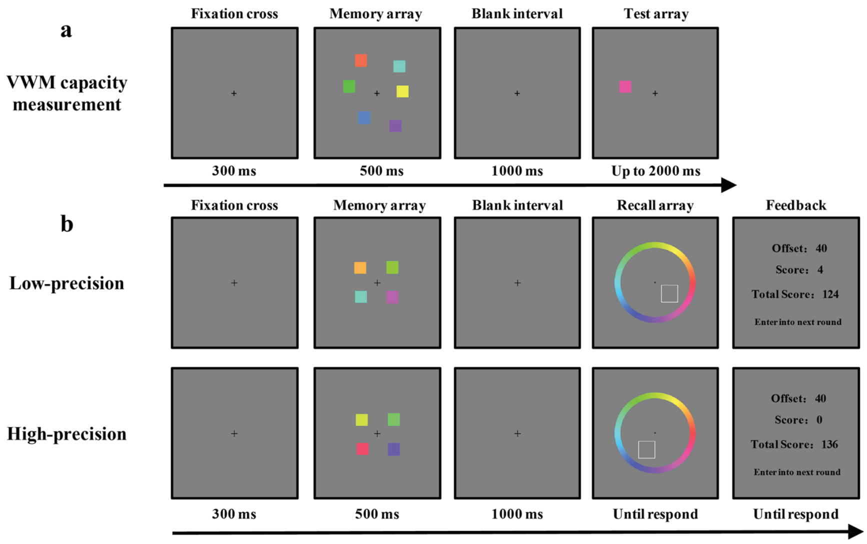

Figure 1. Experimental procedures of Experiment 1. (**a**) Experimental procedure used for the VWM capacity measurement. (**b**) Experimental procedure used in the colour recall task.

consent before participating in the experiment. All procedures were approved by the Ethics Committee of the Liaoning Normal University, China, to collect data outside the campus (in Minnan Normal University), and conducted in accordance with the Declaration of Helsinki (2008).

Materials. In the change detection task for VWM capacity measurement described below, colour squares (each 0.65° × 0.65°) in the memory array displayed within a 9.8° × 7.3° region around a central fixation cross, with a constraint that the distance between two colours was at least 3.5° (centre-to-centre). The colours were randomly selected from 360 possible colours (1–360, in 1 colour step) in the colour recall task, with colour separated by at least 50 colour steps.

In the colour recall task described below, for the memory array, the colour stimuli were four coloured squares (each 0.9° × 0.9°) presented against a grey background. With a fixation cross in the centre, the colour stimuli were presented at the four corners of an imaginary square with an eccentricity of 3.0°. Then, a set palette of 360 colours in a colour wheel (outer diameter, 7.0°; inner diameter, 5.5°), adopted in a prior study by our group[29], was used for the recall array. The stimuli showed in the memory array were randomly chosen from the colour palette with a minimum distance of 30° in colour space between stimuli in the array of four colours. The whole experiment was conducted in a dark room, with a 19 inch LCD screen (1280 × 768 pixel) for presenting the stimuli, and the distance between the participant and the screen was approximately 60 cm.

Procedure. There were two sessions in the experiment, the VWM capacity measurement session and the colour recall task session. The participants first completed a change detection task to measure their VWM capacities. In this session (VWM capacity measurement), each trial began with a central fixation cross that appeared on the screen for 200 ms. A memory array of six colours was then presented for 500 ms. After a subsequent 1000 ms retention period featuring a blank screen, a test array that lasted for 2500 ms was presented (Fig. 1a). A test coloured square was presented at the location of one of the sample squares in the memory array. Participants were asked to indicate whether the colour of test square was identical in colour to the corresponding item in the memory array, or whether the colour in the corresponding location changed between the memory and test array. Response accuracy was emphasised rather than response speed. The accuracy was recorded for analysis.

After the completion of the VWM capacity measurement, participants had a rest of at least five minutes before beginning the second session. In this session, participants needed to complete a colour recall task with two precision conditions (Fig. 1b). Each trial started with a fixation cross in the centre of the screen, followed by a 500 ms memory of four colour squares. After a 1000 ms retention period, a recall array was presented. The recall array consisted of an outlined square (1.0° × 1.0°) at the location of one of the sample squares in the memory array in addition to a colour wheel. Participants were asked to report the colour of the remembered item at the location of the white square outline by clicking a mouse on the corresponding location on the colour wheel. Participants were given unlimited time to respond. Then, feedback that contained three values was provided to participants, the "Offset" value, "Score" value and "Total Score" value. The "Offset" value represented the absolute value of the difference between their reported colour value and the actual colour value of the test sample square. The "Score" value represented the scores earned by participants in this trial. The "Total Score" value represented the scores they had accumulated in this condition of the experiment. Participants were encouraged to get higher scores in the colour recall task. The precision (low- and high-precision) conditions were manipulated by varying the rule of the reward scheme. In the low-precision condition, participants were asked to memorise colours in a low-precision way, and earned four scores if their offset was less than 60° in colour space but earned nothing for the offset between 60° and 100° in colour space. In order to encourage participants to memorise as many items as possible in the low-precision condition, participants were penalised two scores for wild guesses (offsets more than 100° in colour space). In the high-precision condition, participants were asked to memorise colours in a high-precision way, and earned six scores if their offset was less than 20° in colour space but earned nothing otherwise. At the beginning of each condition, participants had 100 points as the original score. They were fully informed of the rules of the reward scheme in each condition before the task.

There were 100 trials in the VWM capacity measurement session. In the colour recall task session, the order of the precision conditions was counterbalanced across participants. Each precision condition included 280 trials. There were seven 30-second breaks within-blocks and a 2-min break between the low- and high-precision blocks. Before each block, participants needed to finish at least 24 practice trials to understand the rules. The entire experiment lasted for approximately one hour.

Data analysis. For each participant in the VWM capacity measurement session, we measured the VWM capacity by using Cowan's K formula: $K = N \times (H - F)$, where K represents the VWM capacity, N represents the number of displayed colours, H represents the hit rate, and F represents the false alarm rate[30]. Similar to previous VWM studies[13,14,18,31], the median split was used to divide participants into different VWM capacity groups.

In the colour recall task session, it may have taken a certain amount of time for forming an appropriate strategy based on the task feedback in different conditions. The same method was used here as that used in Ye, *et al.*'s[21] study, where the first 80 trials in each block were not included because participants need to take a certain amount of time for forming an appropriate strategy based on the task feedback in different conditions. Thus, the results were only calculated based on the last 200 trials. The offset in each trial was calculated by subtracting the recalled colour (the value in colour space) from the target colour.

The data were fitted with the standard mixture model to independently measure the SD (circular standard deviation of a normal distribution, inversely related to the precision of the representations) and G (guess rate) of the representations stored in VWM[32]. The mixture model allowed us to estimate the correct memory rate (P) that the target item was correctly recalled from VWM as $1 - G$. Data analysis was performed using the MemToolbox[33]. The standard mixture model was fitted to individual data in different precision conditions, respectively. Since the precision is inversely related to the variance, we used the SD (inversely related to the precision) as the memory precision index and used the P (i.e., $1 - G$) as the memory number index. Besides, we also used the swap model[34] to fit the data, as the outcomes from statistical tests of mixture model parameters and swap model parameters are substantially identical (Supplemental Materials).

For the individual level analysis, we defined the voluntary trade-off magnitude in the VWM precision index (SDT) as

$$\mathrm{SDT} = \frac{\mathrm{SD}(low) - \mathrm{SD}(high)}{\mathrm{SD}(low)}$$

and, defined the voluntary trade-off magnitude in the VWM number index (PT) as

$$\mathrm{PT} = \frac{P(low) - \mathrm{P}(high)}{P(low)}$$

Then, we merged these two indexes (assuming equal weighting) and calculated a general voluntary trade-off index (GT), which was defined as

$$\mathrm{GT} = \frac{\mathrm{SD}(low) - \mathrm{SD}(high)}{\mathrm{SD}(low)} + \frac{P(low) - \mathrm{P}(high)}{P(low)}$$

Where SD(*low*) and SD(*high*) are the precision index in the low- and high-precision conditions, and P(*low*) and P(*high*) are the correct memory rate in the low- and high-precision conditions. If the participants allocated resources flexibly in the high-precision conditions, resulting in remembering fewer items, this would make $P(low) > P(high)$, which would obtain a positive PT. However, the items remembered would be maintained more precisely, meaning $SD(low) > SD(high)$ (because the SD value is inversely correlated to precision, a larger SD value means a lower precision), which would obtain a positive SDT. By dividing the numerators by the low-precision value, the equations of SDT and PT could minimise the inter-participant variance of the precision and number indexes and indicate the change degree of the indexes in high-precision condition to that in low-precision condition. GT value, a combined measure that contains both precision and number index, is thus the extent to which participant did trade-off according to the task requirements.

For the population level analysis, a significance level of $p < 0.05$ was used for all variables and was introduced as the criterion for the post hoc analysis in the repeated measures ANOVAs. Paired two-tailed t-tests were conducted for comparison in both capacity groups. Also, Bayes factor analysis was conducted to avoid that the null results were observed by chance[35]. We used the JASP 0.7 statistics package to calculate the Bayes factors[36]. The suggested default priors from JASP have been chosen for the Bayesian analysis. The Bayes factor (BF_{10}, an odds ratio for the alternative/null hypotheses, values < 1 favour the null hypothesis and values > 1 favour the alternative hypothesis) provides a continuous measure of how much more likely the data are under the alternative hypothesis compared with the null hypothesis. In our study, the null hypothesis was that there was no difference between two precision conditions, while the alternative hypothesis was that there was a difference between them. For instance, a BF_{10} of

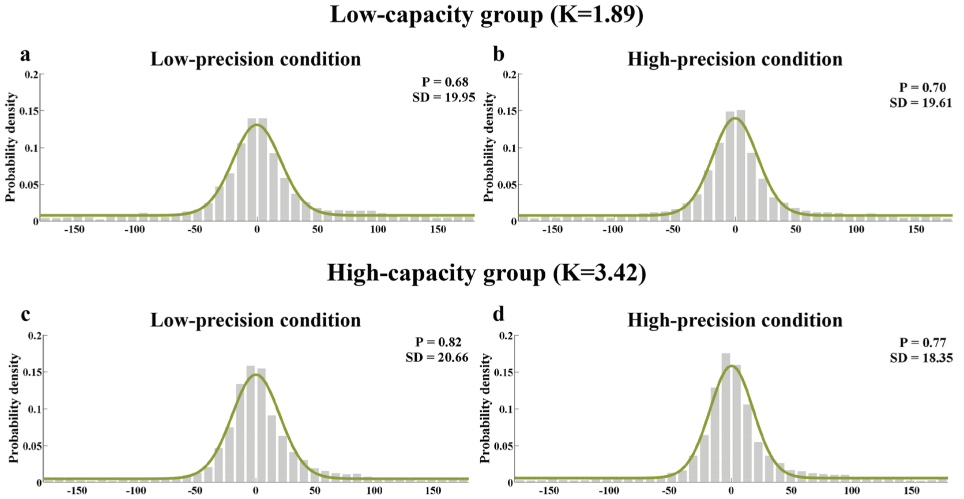

Figure 2. Model-fit results of Experiment 1. The graphs show the model-fit results of the low-capacity group in the top row and the high-capacity group in the bottom row. The results show probability density functions for the offset of responses in the (**a**) low-precision condition in the low-capacity group, (**b**) high-precision condition in the low-capacity group, (**c**) low-precision condition in the high-capacity group, and (**d**) high-precision condition in the high-capacity group. The mean memory number index (P) and precision index (SD) are also shown for each condition.

0.5 represents that the data are 2 times likely under the null hypothesis than the alternative hypothesis, and a BF_{10} of 2 represents that the alternative hypothesis is 2 times more likely than the null hypothesis.

For the individual level analysis, as we mentioned above, we expected that if VWM capacity affects the trade-off ability, there should be a positive correlation between VWM capacity (K) and trade-off ability (SDT, PT and GT). Participants with higher VWM capacity should have better trade-off ability. On the contrary, if VWM capacity does not affect the trade-off ability, there should be no correlation between VWM capacity and trade-off ability. Therefore, we used the one-tailed tests in the correlation analysis based on our expectation.

Results and Discussion. *Results of different capacity groups (population level).* Participants were divided into different groups by the median split of their VWM capacity. A high VWM capacity group ($K = 3.42 \pm 0.56$) and a low VWM capacity group ($K = 1.89 \pm 0.58$), resulting in 13 participants in each group.

We fitted the mixture model to the aggregate data (Fig. 2) and averaged parameters of the mixture model for individual fits. The results of Experiment 1 are found in Fig. 3.

A two-way ANOVA with precision condition (low-precision vs high-precision) and VWM capacity (low VWM capacity vs high VWM capacity) was conducted on the memory precision (SD) and number index (P), respectively. For the precision index (SD), the main effect of precision condition was significant, $F(1,24) = 13.015$, $p < 0.01$, $\eta^2 = 0.352$, but the main effect of VWM capacity was non-significant, $F(1,24) = 0.062$, $p = 0.805$, $\eta^2 = 0.003$. The interaction between the precision condition and VWM capacity was significant, $F(1,24) = 7.097$, $p < 0.05$, $\eta^2 = 0.228$. For the memory number index (P), the main effect of VWM capacity was significant, $F(1,24) = 4.959$, $p < 0.05$, $\eta^2 = 0.171$, but the main effect of precision condition was non-significant, $F(1,24) = 0.812$, $p = 0.377$, $\eta^2 = 0.033$. The interaction between the precision condition and VWM capacity was significant, $F(1,24) = 6.625$, $p < 0.05$, $\eta^2 = 0.216$.

Follow-up pairwise comparisons showed that, for the high VWM capacity group the VWM precision was higher for the high-precision condition compared to the low-precision condition, $t(12) = 4.102$, $p < 0.001$, *Cohen's d* = 0.86, $BF_{10} = 28.57$ for SD. Besides, the memory number in the high-precision condition was less than that in the low-precision condition, $t(12) = 2.621$, $p < 0.05$, *Cohen's d* = 0.47, $BF_{10} = 3.03$ for P. In contrast, for the low-capacity group, there was neither VWM precision difference nor memory number difference between high-precision and low-precision conditions, $t(12) = 0.732$, $p = 0.478$, *Cohen's d* = 0.11, $BF_{10} = 0.35$ for SD; $t(12) = 1.117$, $p = 0.286$, *Cohen's d* = 0.13, $BF_{10} = 0.47$ for P.

In line with our expectation, these results support the hypothesis that VWM capacity affects the trade-off ability. The results suggest that for the high-capacity group, participants memorise fewer colours but with higher precision in the high-precision condition compared to the low-precision condition. However, for the low-capacity group, there was no significant difference in the precision or number between two precision conditions.

Correlation results (individual level). We measured the relationship between the K (VWM capacity) and SDT (trade-off magnitude in VWM precision) value, K and PT (trade-off magnitude in VWM number) value, K and GT (general trade-off magnitude) value. The SDT, PT, GT values were plotted as a function of each's VWM capacity in Fig. 4a–c.

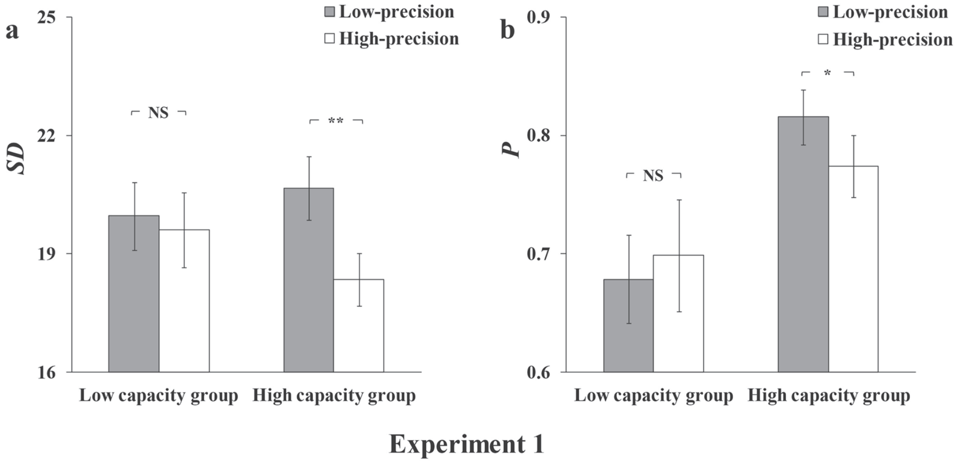

Figure 3. Results for the low- and high-capacity groups in Experiment 1. The graph shows both low-capacity and high-capacity groups' results, with (**a**) the memory precision index (SD) and (**b**) memory number index (P) presented separately for the low-precision and high-precision conditions. Error bars are standard error of the mean. NS = non-significant; *p < 0.05; **p < 0.01.

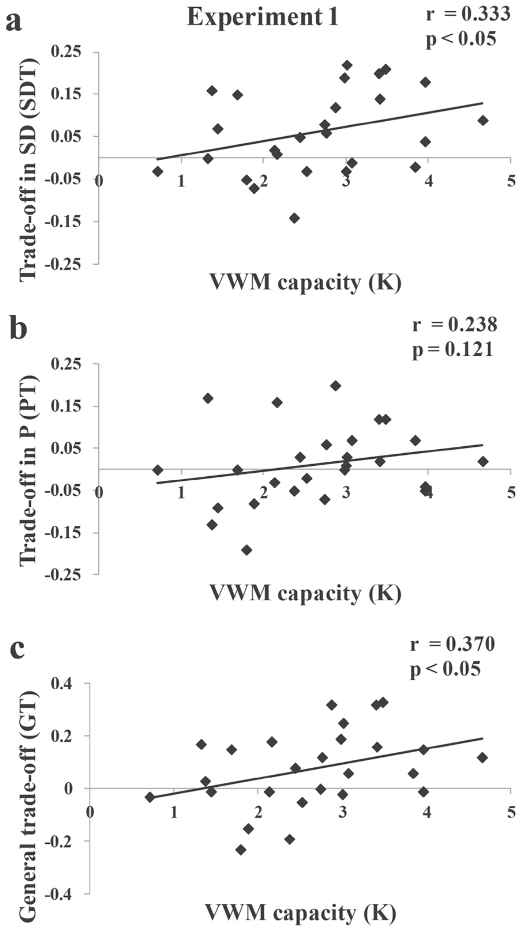

Figure 4. Correlation results of Experiment 1. (**a**) Correlation between VWM capacity(K) and trade-off magnitude in precision (SDT), (**b**) Correlation between VWM capacity(K) and trade-off magnitude in number (PT), and (**c**) Correlation between VWM capacity(K) and general trade-off index(GT).

The K and SDT were positively correlated ($r = 0.333$, $p < 0.05$, one-tailed): low VWM capacity participants showed low trade-off magnitude in VWM precision, and high VWM capacity participants produced much higher trade-off magnitude in VWM precision. There was a small positive correlation trend between the K and PT, but it was not statistically significant ($r = 0.238$, $p = 0.121$, one-tailed). More importantly, the VWM capacity and GT were positively correlated ($r = 0.370$, $p < 0.05$, one-tailed): low VWM capacity participants showed low general trade-off magnitude, and high VWM capacity participants produced much higher general trade-off magnitude.

In the results of the population level analysis, we found that there was an impact of VWM capacity on the trade-off ability. Participants in the high VWM capacity group were able to trade off the VWM precision and number voluntarily, but those in the low VWM capacity group had difficulty in a flexible trade-off. More importantly, in the individual level analysis, the results of Experiment 1 showed that the VWM capacity of the individual was positively correlated with the trade-off ability when participants have enough consolidation time to trade off the VWM precision and number. The pattern of results found here seems to be consistent with the results found by Vogel, *et al.*[13], suggesting that low VWM capacity individuals failed to filter out the distractors. In other words, it might take extra effort to consolidate the memory selectively. Low VWM capacity individuals might forgo the extra selective processing because it is self-defeating or uncomfortably effortful for them[17]. The extra processing may also encourage low VWM capacity participants to skip the voluntary trade-off process in our study.

According to the two-phase model and our hypothesis, the trade-off pattern of individuals may be different with different critical values of duration/set size. Consequently, we wanted to verify this in Experiment 2 with a smaller ratio of duration/set size.

Experiment 2

The purpose of Experiment 2 was to verify whether the smaller ratio of duration/set size would cause the failure of the voluntary trade-off for most participants (and consequently lack of relation between voluntary trade-off magnitude and VWM capacity) as suggested by the two-phase model. We used the same procedure as Experiment 1 but reduced the exposure duration from 500 ms to 200 ms (the set size remained as four), generating a ratio of duration/set size of 50 ms/item. It is expected that participants could not voluntarily trade off for the small ratio of duration/set size as they need more time to enter the late allocation phase.

Methods.

Participants. Twenty-six new undergraduate students (20.99 ± 1.07 years old, age range 19–24 years, 23 females) were recruited from the participant pool at the Minnan Normal University. All procedures were approved by the Ethics Committee of the Liaoning Normal University, China, to collect data outside the campus (in Minnan Normal University), and conducted in accordance with the Declaration of Helsinki (2008).

Procedure and data analysis. Except that the exposure duration of the memory array in the colour recall task decreased from 500 ms to 200 ms, the procedure and data analysis of Experiment 2 was identical with that of Experiment 1.

Results and Discussion.

Results of different VWM capacity groups (population level). As in Experiment 1, we divided 26 new participants based on their VWM capacity estimated in Experiment 2 into two different groups, a high VWM capacity ($K = 3.24 \pm 0.59$) and a low-capacity group ($K = 1.81 \pm 0.48$), resulting in 13 participants in each group respectively.

Again, the mixture model was fitted to the aggregate data (Fig. 5) and averaged parameters of the mixture model for individual fits. The results were shown in Fig. 6.

A two-way ANOVA with precision condition (low-precision vs high-precision) and VWM capacity (low VWM capacity vs high VWM capacity) was conducted on the memory precision (SD) and number index (P), respectively. For the memory precision index (SD), the main effects of precision condition, $F(1,24) = 0.883$, $p = 0.357$, $\eta^2 = 0.035$, and VWM capacity, $F(1,24) = 0.129$, $p = 0.722$, $\eta^2 = 0.005$, were non-significant. Also, there was no significant interaction effect between the precision condition and VWM capacity, $F(1,24) = 0.053$, $p = 0.820$, $\eta^2 = 0.002$. For the memory number index (P), similar to the result pattern of memory precision index, no significant main effect was found neither for precision condition, $F(1,24) = 0.002$, $p = 0.967$, $\eta^2 = 0.000$, nor for VWM capacity, $F(1,24) = 1.604$, $p = 0.218$, $\eta^2 = 0.063$. Also, the interaction effect between the precision condition and VWM capacity was non-significant, $F(1,24) = 1.827$, $p = 0.189$, $\eta^2 = 0.071$.

The results suggest that for both high and low VWM capacity group, participants maintained the same number of VWM representations with the same precision in different precision conditions. In line with our expectation, that is, with a small ratio of duration/set size, both low- and high-capacity groups did not show a trade-off ability as it appeared in Experiment 1. In other words, with a smaller ratio, most people can only allocate VWM resource in a stimulus-drive (involuntary) manner regardless of their VWM capacity.

In addition, a mixed-factor ANOVA was conducted respectively for on the memory precision (SD) and number index (P), with the precision condition (low-precision vs high-precision) as a within-subject factor, and the VWM capacity (low VWM capacity vs high VWM capacity) and experiment (Experiment 1 vs Experiment 2) as between-subject factors For the memory precision index (SD), a significant main effect of precision condition was found, $F(1,48) = 4.135$, $p < 0.05$, $\eta^2 = 0.079$, but no other significant main effect nor interaction was found (all $ps > 0.294$). For the memory number index (P), the main effect of VWM capacity was significant, $F(1,48) = 6.025$, $p < 0.05$, $\eta^2 = 0.112$, and there was a significant interaction effect across precision condition, VWM capacity and experiment, $F(1,48) = 5.909$, $p < 0.05$, $\eta^2 = 0.110$, but neither other significant main effects nor interaction was found (all $ps > 0.112$).

The results of ANOVA across experiments showed that there was a significant interaction between two precision conditions, VWM capacity and experiment for the number index, but no significant interaction for the precision index. However, in Experiment 1 there was a significant positive correlation between VWM capacity

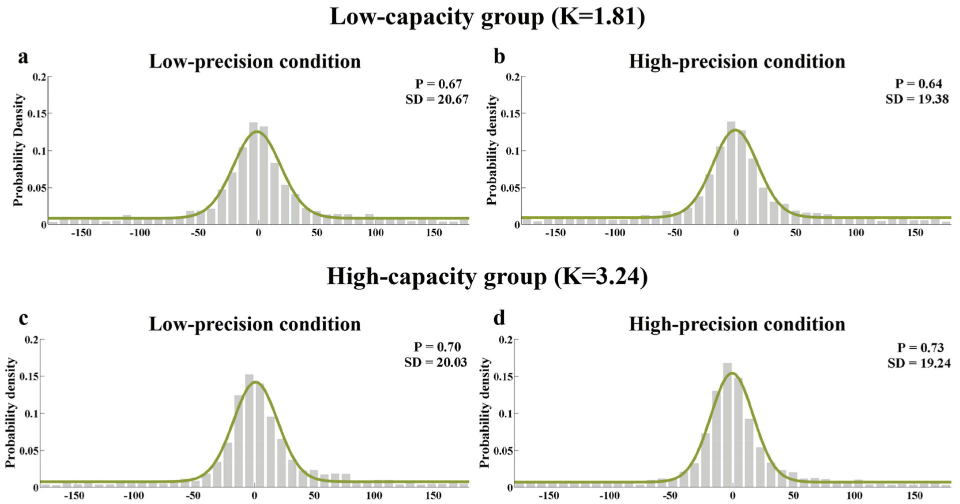

Figure 5. Model-fit results of Experiment 2. The graphs show the model-fit results of the low-capacity group in the top row and the high-capacity group in the bottom row. The results show probability density functions for the offset of responses in the (**a**) low-precision condition in the low-capacity group, (**b**) high-precision condition in the low-capacity group, (**c**) low-precision condition in the high-capacity group, and (**d**) high-precision condition in the high-capacity group. The mean memory number index (P) and precision index (SD) are also shown for each condition.

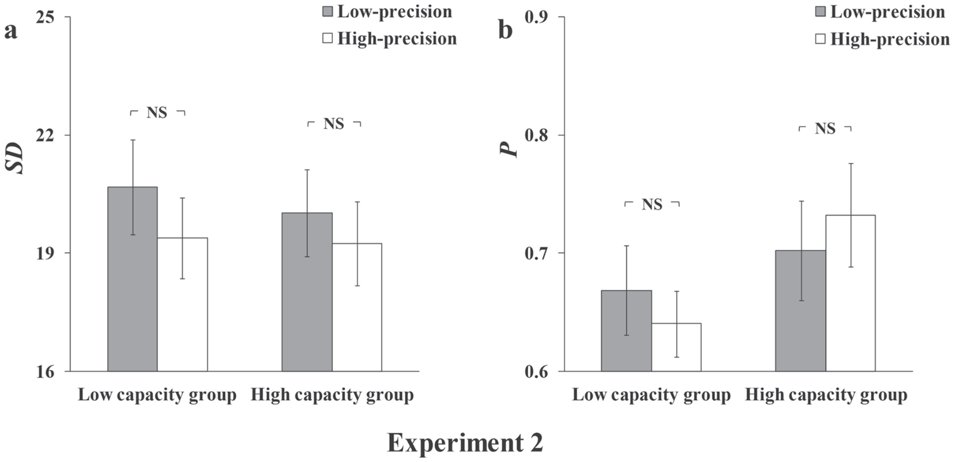

Figure 6. Results for the low- and high-capacity groups in Experiment 2. The graph shows both low-capacity and high-capacity groups' results, with (**a**) the memory precision index (SD) and (**b**) memory number index (P) presented separately for the low-precision and high-precision conditions. Error bars are standard error of the mean. NS = non-significant.

and trade-off magnitude in precision, but no significant positive correlation between VWM capacity and trade-off magnitude in number. These different result patterns may be due to the different variability of number index and precision index, the difference of number index was more evident in the population level analysis, on the contrary, the difference of precision was more evident in the individual level analysis. Therefore, we respectively reported the results of the population level analysis and individual level analysis. It would help us to have a more comprehensive understanding of the relationship between VWM capacity and voluntary trade-off ability.

Correlation results (individual level). Again, we measured the relationship between the K (VWM capacity) and SDT (trade-off magnitude in VWM precision) value, K and PT (trade-off magnitude in VWM number) value, K and GT (general trade-off magnitude) value. The SDT, PT, GT values were plotted as a function of each's VWM capacity in Fig. 7a–c. The results showed no correlations between the K and SDT ($r = -0.080$, $p = 0.348$, one-tailed), K and PT ($r = 0.054$, $p = 0.396$, one-tailed), K and GT ($r = -0.031$, $p = 0.440$, one-tailed).

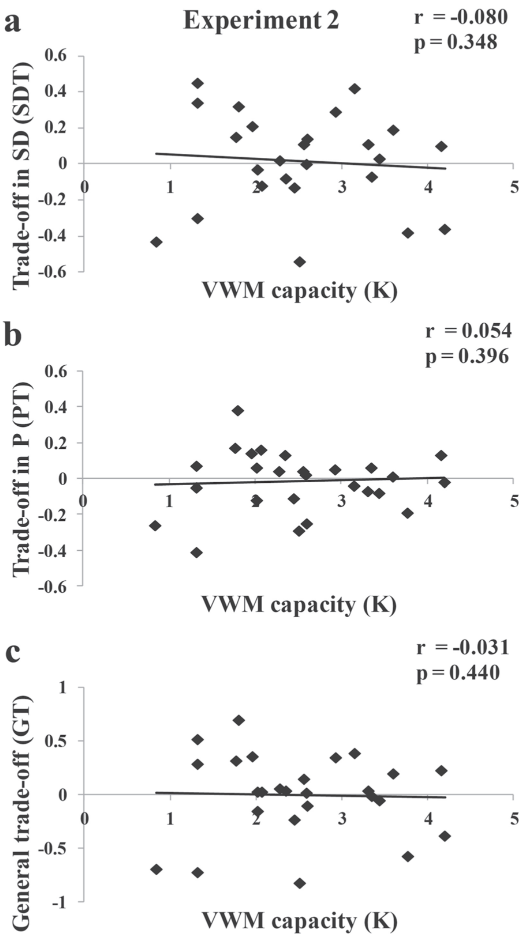

Figure 7. Correlation results of Experiment 2, (**a**) Correlation between VWM capacity (K) and trade-off magnitude in precision (SDT), (**b**) Correlation between VWM capacity (K) and trade-off magnitude in number (PT), and (**c**) Correlation between VWM capacity (K) and general trade-off index (GT).

The results of both population level and individual level analyse in Experiment 2 suggest that regardless of the VWM capacity, participants could not voluntarily trade off the VWM precision and number under a small ratio of duration/set size condition. The present evidence supports that the voluntary trade-off failed in Experiment 1 of Ye, *et al.*'s[21] study only because of insufficient exposure duration. Thus, the result further verifies the two-phase model.

General Discussion

Experiment 1 showed, with a high ratio of duration/set size, that high VWM capacity participants were able to adjust memory precision flexibly according to task requirements, while low VWM capacity participants failed. More importantly, the VWM capacity of the individual was positively correlated with the ability of voluntary trade-off when most participants, for a given set size, have enough consolidation time to trade off the VWM precision and number. Following the previous demonstration that the individual's VWM capacity could affect the ability of attention control to filter distractors[11,13], our work showed that VWM capacity is also related to attention control in VWM task in allowing a voluntary trade-off between VWM precision and number, that is, the ability of voluntary VWM resource allocation. Although many previous studies have explored whether individuals can voluntarily trade off the VWM precision and number[19–21,23], based on our knowledge, the current study provides the first evidence that there is a correlation between the ability of voluntary trade-off and the VWM capacity when the value of duration/set size is large enough (larger than the critical value of 100 ms/item). For participants with low VWM capacity who showed a weaker trade-off ability, the resource allocation is mainly in the form of a stimulus-driven manner, while for participants with high VWM capacity, they can take extra effort to allocate resource to trade off the precision and number voluntarily. In contrast, in Experiment 2, when the ratio of duration/set size was only 50 ms/item (well below the critical value of 100 ms/item), the results showed that regardless of the VWM capacity, most participants could not voluntarily trade off the VWM precision and number. In this case, there was no relation between VWM capacity and voluntary trade-off ability.

In the present study, we not only reported the results of the population level analysis on the memory precision and number index respectively as previous studies[21,23,25,26,28], but also the results of the individual level analysis by merging precision and number index. The population level analysis for the precision index did not reach significance in a between-experiment analysis (i.e., the three-way interaction of precision condition × capacity group × experiment on the precision index). This may reflect some potential problems of the population level analysis, such as the relying solely on a median split to divide capacity groups for data analysis (while useful for illustrative purposes) might be problematic from a statistical standpoint. Thus, the continuous measure of performance (e.g., individual level analysis) may be a more appropriate approach here. The discussion below is mainly based on the correlation results within the separate experiments.

Accounting for our results and others published with the two-phase model. In general, the results from the current study are consistent with the two-phase model proposed by Ye, *et al.*[21], suggesting that for a given set size, when the consolidation time is extremely short, regardless of VWM capacity, individuals cannot allocate resources voluntarily. However, when the consolidation time is long enough, individuals can allocate resources voluntarily, and the ability to allocate resources is highly related to their VWM capacity.

In previous studies about the voluntary trade-off between VWM precision and number, many studies supported the voluntary trade-off used the orientation as the stimulus[19–26], but most of the studies using colour materials failed to find evidence that participants could trade off voluntarily[22,23,25]. Therefore, one might think that the stimulus property (orientation vs colour) might be the determining factor for the patterns of the results. After all, orientation is a boundary feature while the main property of a colour stimulus is its surface feature[37]. The consolidation mechanisms for the orientation and colour materials could be different. For example, a series of studies have shown that the memory consolidation bandwidth is different between colour and orientation feature[38–43]. Thus, there is a possibility that individuals could show a lack of voluntary trade-off ability for colour materials. However, the results of our Experiment 1 showed that there was a voluntary trade-off for colour materials (also see Fougnie, *et al.*[26]). These results suggest that, regardless of the stimulus property, the individuals could voluntarily trade off the VWM precision and number with long exposure duration. Moreover, it should be noted that, as it showed in our Experiment 2, with a small ratio of duration/set size, the individuals could not trade off voluntarily in the condition. Therefore, although the two-phase model was proposed in the study using orientation materials as stimulus[21], the combined results of our Experiment 1 and 2 suggest that the model is also suitable for colour materials.

It is important to point out that, as mentioned in the introduction, there were still two pieces of contrary evidence (2/25 experiments) which did not correspond to the predictions of the two-phase model. The first contrary evidence was the result of a supplementary experiment in Fougnie, *et al.*'s[26] study. Although the two-phase model could well predict the results of their Experiment 1 and 2 (which could trade off the VWM precision and number when participants memorize five colours at 1200 ms exposure duration), they conducted a quick supplementary experiment and found that participants could also trade off the VWM precision and number when they needed to memorize five colours at 200 ms. Thus, their study suggested that participants could trade off VWM precision and number without being affected by the length of exposure duration. The second contrary evidence was Experiment 3 in Ramaty and Luria's[28] study. Ramaty and Luria[28] conducted a follow-up study of Fougnie, *et al.*[26]'s study, but they found different results from Fougnie, *et al.*'s[26] study. In Ramaty and Luria's[28] study, they firstly repeated that participants could trade off the VWM precision and number when they need to memorise five items at 1200 ms exposure duration (Experiment 1). Then they found that this trade-off disappeared when the exposure duration decreases from 1200 ms to 300 ms (Experiment 2). Although the results mentioned above (the first two experiments in Ramaty and Luria's[28] study) could be predicted by the two-phase model, Experiment 3 in Ramaty and Luria's[28] study showed that the trade-off disappeared when participants need to memorise five items at 1200 ms exposure duration with an articulatory suppression. Thus, they suggested that an effective trade-off between VWM precision and number was due to verbal encoding instead of VWM processing, and the verbal encoding was mediated by long encoding durations. Unlike the present study, both of these studies[26,28] asked participants to conduct a standard task (for the high-precision condition) and a get-them-all task (for the low-precision condition) to induce a trade-off. In the standard task, participants were asked to report only one colour out of five colours that appeared in the memory array, but in the get-them-all task, participants were asked to report all five colours. Compared with the standard task, participants had more motivation to maintain all five colours simultaneously in the get-them-all task. Because memorising five colours are beyond the average of individual VWM capacity, participants were not able to merely use the VWM encoding to complete the get-them-all task, which leads to the participants may use verbal encoding as a strategy to improve the performance, thus producing a stronger trade-off effect. However, the verbal encoding hypothesis could not explain our current results because of the following reasons. Firstly, in our study, the response requirements were the same in low- and high-precision conditions. Even if the verbal encoding can assist memory, participants should use verbal coding to help to memorise under both conditions. Thus, the effect of verbal encoding should be counteracted by calculating trade-off indexes. Secondly, if the trade-off was caused by using verbal encoding to memorise items strategically, we should be able to observe that low VWM capacity participants could also trade off effectively as high VWM capacity participants in our Experiment 1. Thirdly, verbal encoding requires a long retention interval or exposure duration. For example, in Experiment 4 of Souza and Skora's[44] study, they found that the articulatory suppression impaired the performance of the VWM task when the four colours were present at a 250 ms exposure duration followed by a 3000 ms retention interval. However, the articulatory suppression did not affect the performance of the VWM task when the four colours were present at a 250 ms exposure duration followed by a 1000 ms retention interval. In Vogel, *et al.*'s[45] study, they found that there was no difference in the memory performance between the 100 ms exposure duration and 500 ms exposure duration when the participants needed to memorise four colours. Moreover, the VWM performance did not change because of the additional verbal working memory load. This evidence suggests that verbal encoding has a limited impact on VWM performance in our study, which used 500 ms or less exposure duration and 1000 ms retention interval. Therefore, the trade-off in the present study is mainly caused by the reallocation of VWM resources, instead of verbal encoding.

Critical value of duration/set size may be related to memory consolidation. Both the current results and results found in Ye, *et al.*'s[21] study demonstrated the importance of the critical value of duration/set size as a factor in determining whether voluntary trade-off would occur. The current results showed that when a ratio of 125 ms/item was adopted for presenting stimuli, participants with high VWM capacity could flexibly adjust the trade-off according to task requirements. However, participants could not voluntarily adjust the trade-off regardless of the VWM capacity when the ratio of 50 ms/item was adopted. According to the two-phase model, whether individuals can start the late resource allocation phase is mainly depends on their early consolidation processing. The consolidation process, the initial formation of VWM representations, has been studied for decades[38,46–49]. Vogel, *et al.*'s[48] study showed that the VWM consolidation rate of the colour stimulus was about 50 ms/item[48]. A recent study by our group found similar results that participants spent an average of 60 ms to consolidate a colour stimulus into their VWM[38]. Thus, these results imply that the rate of duration/set size allowing individuals to trade off voluntarily is probably related to the time spent on VWM consolidation of the stimuli, and the voluntary trade-off between quality and quantity only occur when the ratio for presenting stimuli is much larger than the rate of consolidation.

Trade-off issue in VWM models. It is important to point out that the trade-off of precision and number can take place in two forms. Participants can opt to increase memory precision by sacrificing the number of items remembered. A more interesting question would be whether participants can increase the VWM number by sacrificing precision. It is still under debate if such an increase in VWM number can go beyond an upper limit of normal memory capacity[23,26].

For the nature of VWM resource, there are two classes of models: "slot" model and "resource" model. The classical slot model proposes that the number of available resources (considered as "slots") in VWM is limited. The slots can only be used to keep a limited set of discrete items. It means that when all those slots are fully occupied in VWM, no additional items can be further stored into these slots, and the memory precision could not be affected by the number of memory items[30,45,50]. However, a more recent revision of such a model, called slot + average model, states that when the number of stored items did not reach the maximal number of slots, a single item could be stored in multiple slots, leading to an increase in precision of that item[32]. In contrast, flexible resource model suggests a flexible allocation of limited cognitive resources. Allocating more resources to an item will allow greater precision. The trade-off between precision and number can be in two directions: an increase in precision on a small number of items or increase in memory number by sacrificing precision. More importantly, the resource models do not impose an upper limit on memory number[34,51–54]. There have been studies supporting each of the two classes of models mentioned above. The current study was not designed to provide direct support for either model. Instead, we offered a novel perspective suggesting that, for a given set size, the stimulus duration is the determining factor for the voluntary trade-off. The current study utilised the set size of four, which is likely for most participants within their VWM capacity. Future work may introduce tasks requiring participants to memorise a large number of the items above estimated average memory capacity to seek an answer for the question whether there is a limit in storing more items by scarifying precision.

Other contributions to future research. The present study showed that when participants were able to trade off the VWM precision and number voluntarily, the individual's VWM capacity is positively related to the voluntary trade-off ability for VWM precision and number. This result is consistent with the results found in VWM task involving distractors, which suggests that there is a positive correlation between VWM capacity and attention filtering ability[11,13]. However, the attention mechanism invoked in the studies about attention filtering may not be entirely the same as the attention that is invoked in the present study. The mental process involved in ignoring distractors might be primarily contributed by selective attention, which has been widely studied in the interaction between VWM and attention[55–58]. This kind of attention can be classified as external attention[58]. In addition to this, another kind of attention called internal attention also affects VWM performance, which is used by participants in the present study to reallocate resource to achieve a voluntary trade-off between VWM quality and quantity. The impact of internal attention on VWM processing has been generating considerable interest. For example, recent studies suggested that more internal attention resources enable individuals to allocate VWM resources more effectively, thereby improving VWM performance[59]. In addition, individuals can use internal attention to flexibly allocate VWM resources to even a particular dimension of representations[29,60]. Thus, the present study provides an important supplement to the research on the relation between attention and VWM.

It is worth noting that although there have been many studies on trade-off using a mixture model (or other models) fitting[21,23,25,26,28], according to our knowledge, all of them analysed the precision and number index respectively. In the present study, we used GT as a measure to merge the precision and number index to quantify the magnitude of voluntary trade-off. We did not use this paper to argue that the equation of GT is an ideal solution to the trade-off issue in the field, but we believe that future studies on trade-off can further improve the equation of GT to take into account the change of both precision and number. For example, future research could further explore the relationship between individual trade-off ability and attentional filtering ability with a method similar to the GT equation. Therefore, the setup of the combined measure in this paper is a new beginning to quantify the individual's trade-off ability.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author (lq780614@163.com, Qiang Liu) on reasonable request.

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Author Contributions

Q.L. and C.Y. conceived and designed the experiments. C.Y. performed the data acquisition. H.S., C.Y. analyzed the data. H.S., Q.L. and C.Y. interpreted the data. H.S., Q.L. and C.Y. drafted the manuscript. All authors substantively revised and approved the manuscript.

Additional Information

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Working memory capacity affects trade-off between quality and quantity only when stimulus exposure duration is sufficient: Evidence for the two-phase model

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Supplementary Materials

Data fitting results of swap model

In the supplementary materials the swap model (Bays, Catalao, & Husain, 2009) was also used to fit data by using Memtoolbox (Suchow, Brady, Fougnie, & Alvarez, 2013), and then calculated the voluntary trade-off index based on the results of the swap model fitting. The swap model assumes that there are third types of responses (non-target memory responses) in addition to the two types of the standard mixture model (random guess responses and responses based on noisy internal memory). Thus, there are three main parameters in the results of swap model fitting, memory precision index (SD_s), guess rate (G_s) and non-target reported rate (B_s). Then we estimated the memory number index (P_s) by calculating the correct response rate (i.e., 1- G_s - B_s).

Based on the memory precision index (SD_s) and number index (P_s), the voluntary trade-off magnitude in the VWM number index (P_sT) was defined as

$$\mathrm{P_sT} = \frac{\mathrm{P_s}(low) - \mathrm{P_s}(high)}{\mathrm{P_s}(low)}$$

and the voluntary trade-off magnitude in the VWM precision index (SD_sT) was defined as

$$\mathrm{SD_sT} = \frac{\mathrm{SD_s}(low) - \mathrm{SD_s}(high)}{\mathrm{SD_s}(low)}$$

Then, these two indexes were merged and calculated as a general voluntary trade-off index (G_sT), which was defined as

$$\mathrm{G_sT} = \frac{\mathrm{P_s}(low) - \mathrm{P_s}(high)}{\mathrm{P_s}(low)} + \frac{\mathrm{SD_s}(low) - \mathrm{SD_s}(high)}{\mathrm{SD_s}(low)}$$

where P_s(*low*) and P_s(*high*) represent the correct memory rate in the low- and high-precision conditions, and SD_s(*low*) and SD_s(*high*) represent the precision index in the low- and high-precision conditions. G_sT value represents the magnitude of voluntary trade-off.

Correlation results

Experiment 1

The Pearson correlation coefficient was measured between K (VWM capacity) and SD_sT value (trade-off magnitude in VWM precision), K and P_sT (trade-off magnitude in VWM number) value, K and G_sT (general trade-off magnitude) value. The SD_sT, P_sT, G_sT values were plotted as a function of each individual's VWM capacity in Figure 1a-c. The results showed that there was a positively significant correlation between K and SD_sT ($r = 0.362$, $p < 0.05$, one-tailed). There was a small positive correlation trend between the K and P_sT, but it was not statistically significant ($r = 0.175$, $p = 0.196$, one-tailed).. More importantly, the VWM capacity and G_sT were positively correlated ($r = 0.348$, $p < 0.05$, one-tailed).

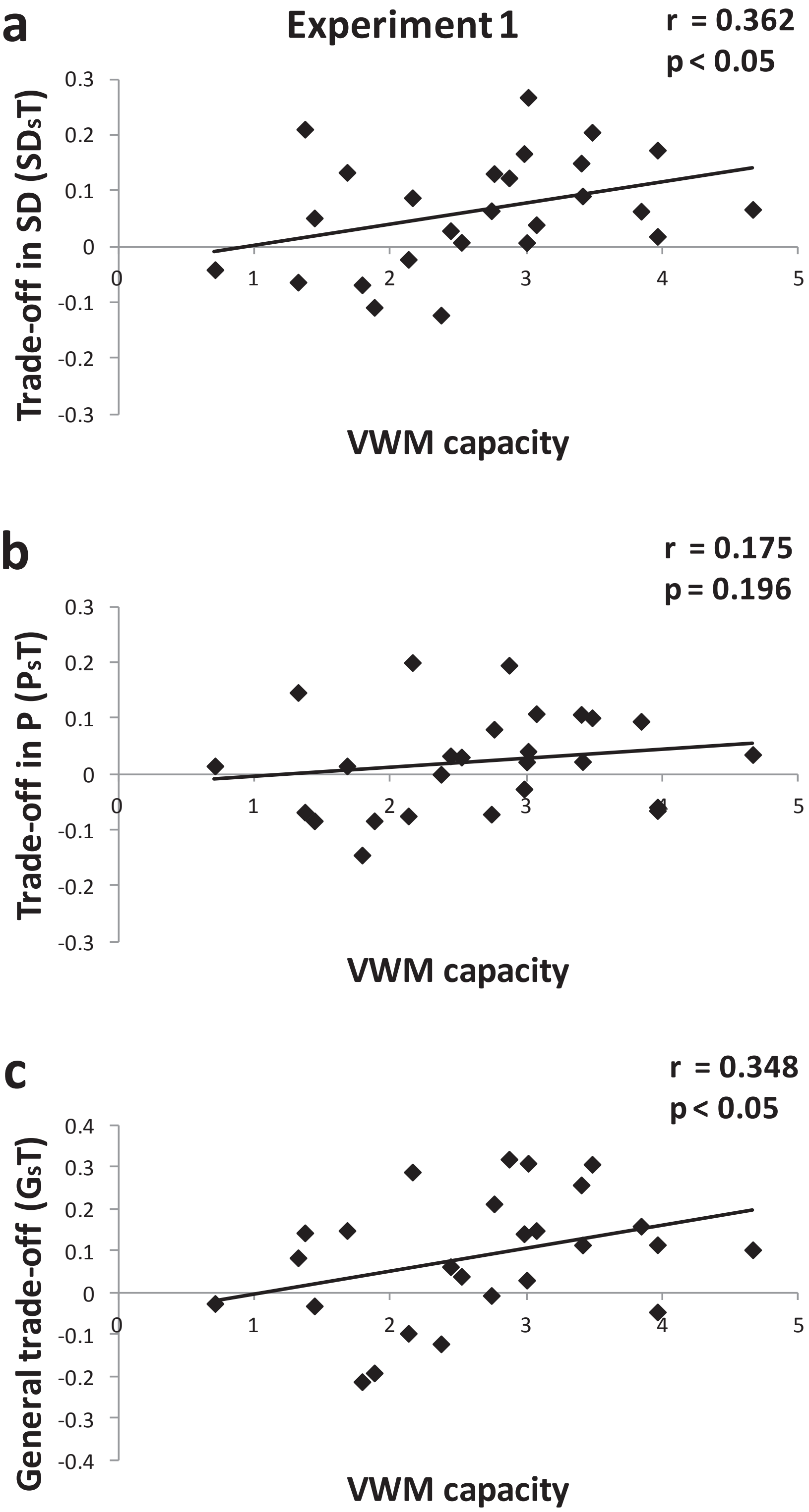

Figure 1. Correlation results based on the swap model fitting in Experiments 1.

(a) Correlation between VWM capacity(K) and trade-off magnitude in precision (SDsT), (b) Correlation between VWM capacity (K) and trade-off magnitude in number (P_sT*), and (c) Correlation between VWM capacity(K) and general trade-off index (*G_sT*).*

Experiment 2

Similar to the analysis used in Experiment 1, in Experiment 2, we measured the relationship between K and SD$_s$T value, K and P$_s$T value, K and G$_s$T value in same way. The SD$_s$T, P$_s$T, G$_s$T values were plotted as a function of each individual's VWM capacity in Figure 2a-c. The results show no correlations between the K and SD$_s$T (r = -0.080, p = 0.350, one-tailed), K and P$_s$T (r = 0.001, p = 0.499, one-tailed), K and G$_s$T (r = -0.054, p = 0.396, one-tailed).

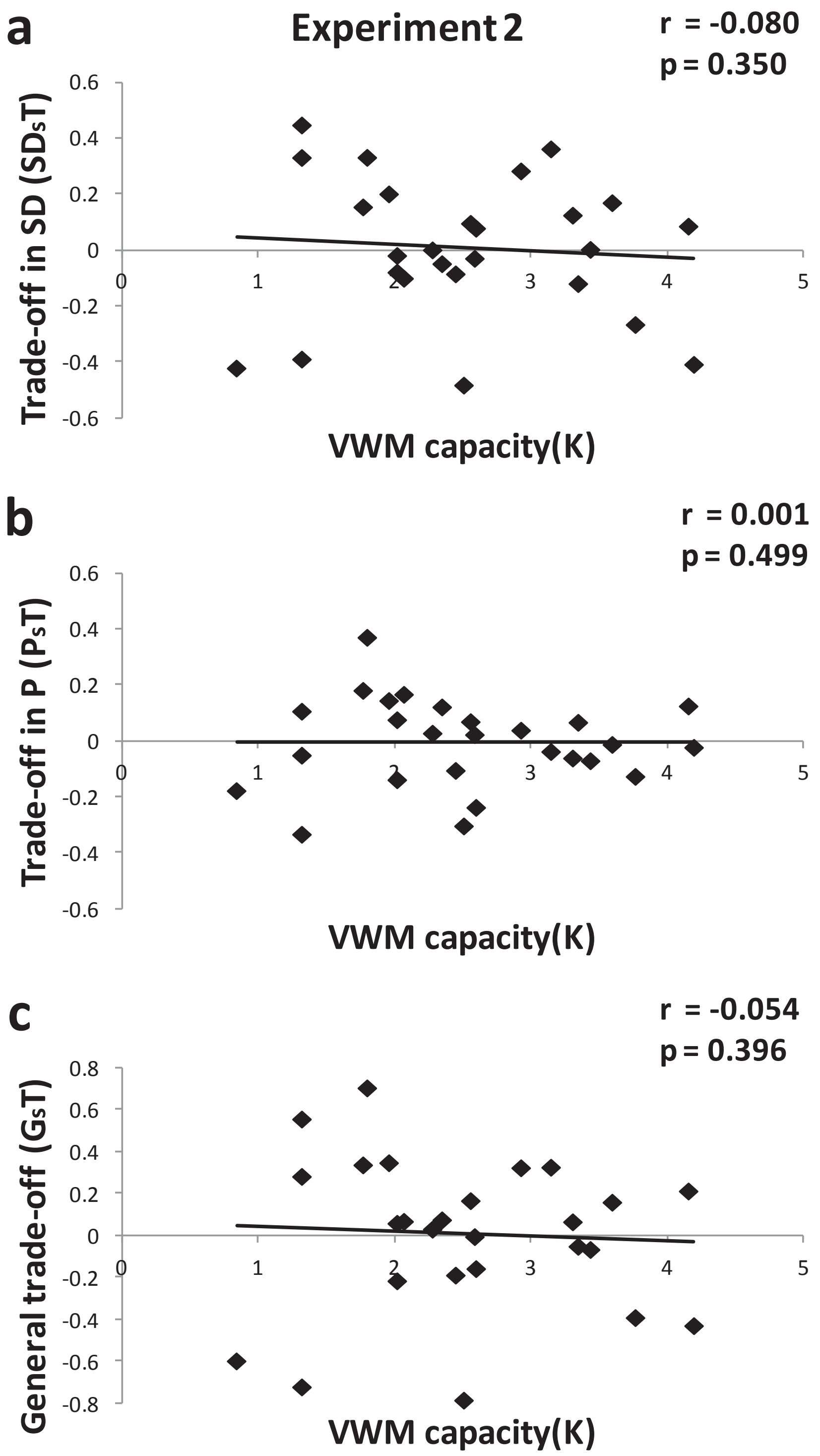

Figure 2. Correlation results based on the swap model fitting in Experiments 2. *(a) Correlation between VWM capacity(K) and trade-off magnitude in precision* (SD_sT)*, (b) Correlation between VWM capacity (K) and trade-off magnitude in*

number (P_sT), and (c) Correlation between VWM capacity (K) and general trade-off index (G_sT).

Results of different VWM capacity groups

Experiment 1

Participants were divided into different groups by the median split of their VWM capacity. A high VWM capacity group (K = 3.42±0.56) and a low VWM capacity group (K = 1.89±0.58), resulting in 13 participants in each group.

The parameters of the swap model (P_s, SD_s) were calculated for individual fits in Experiment 1. The results were shown in Figure 3.

A two-way ANOVA with precision condition (low-precision vs. high-precision) and VWM capacity (low VWM capacity vs. high VWM capacity) was conducted for the the precision index (SD_s), there was a main effect of precision condition [$F(1,24) = 13.816$, $p < .001$, $\eta^2 = 0.365$], but no significant main effect of VWM capacity [$F(1,24) = 0.696$, $p = .413$, $\eta^2 = 0.028$]. The interaction between the precision condition and VWM capacity was significant [$F(1,24) = 8.622$, $p < .01$, $\eta^2 = 0.264$].

A two-way ANOVA with precision condition (low-precision vs. high-precision) and VWM capacity (low VWM capacity vs. high VWM capacity) was also conducted for the the memory number index (P_s), there was a main effect of VWM capacity [$F(1,24) = 4.450$, $p < .05$, $\eta^2 = 0.156$], but no significant main effect of precision condition [$F(1,24) = 1.806$, $p = .192$, $\eta^2 = 0.070$]. The interaction between the precision condition and VWM capacity was significant [$F(1,24) = 4.384$, $p < .05$, $\eta^2 = 0.154$].

Follow-up pairwise comparisons showed that, for the high VWM capacity group the VWM precision in the high-precision condition was higher than that in the low-precision condition [$t(12) = 4.748$, $p < .001$, *Cohen's d* = 0.94 for SD_s]. Besides, the memory number in the high-precision condition was less than that in the low-precision condition [$t(12) = 2.485$, $p < .05$, *Cohen's d* = 0.47 for P_s]. In contrast, for the low-capacity group, there was neither VWM precision difference nor memory number difference between high-precision and low-precision conditions [$t(12) = 0.547$, $p = .594$, *Cohen's d* = 0.09 for SD_s; $t(12) = 0.519$, $p = .613$, *Cohen's d* = 0.06 for P_s].

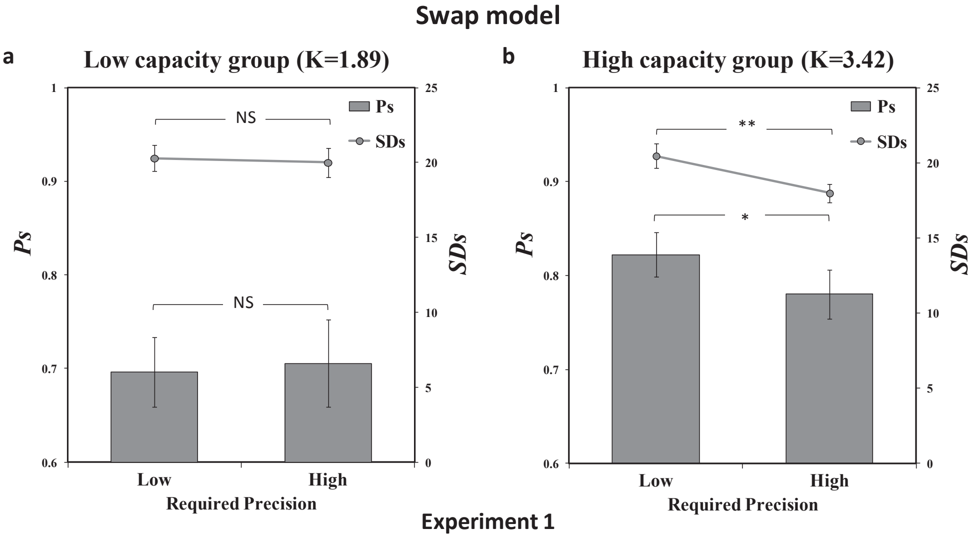

Figure 3. Swap model fitting results for the low VWM capacity group and high VWM capacity group in Experiment 1. *The graph shows the low-capacity (a) and high-capacity (b) groups' results, with the mean correct memory rate and the standard deviation presented separately for the low-precision and high-precision conditions. Error bars are standard error of the mean. NS = non-significant; * = p < 0.05; ** = p < 0.01.*

Experiment 2

As Experiment 1, we divided 26 new participants based on their VWM capacity estimated in Experiment 2 into two different groups, a high VWM capacity (K = 3.24±0.59) and a low-capacity group (K = 1.81±0.48), resulting in 13 participants in each group respectively.

Again, the parameters of the swap model (P_s, SD_s) were calculated for individual fits in Experiment 1. The results were shown in Figure 4.

A two-way ANOVA with precision condition (low-precision vs. high-precision) and VWM capacity (low VWM capacity vs. high VWM capacity) was conducted for the the memory precision index (SD_s). There were no significant main effects of precision condition [$F(1,24) = 0.645$, $p = .430$, $\eta^2 = 0.026$] and VWM capacity [$F(1,24) = 0.014$, $p = .906$, $\eta^2 = 0.001$]. Also, the interaction effect between the precision condition and VWM capacity was non-significant [$F(1,24) = 0.204$, $p = .656$, $\eta^2 = 0.008$].

For the the memory number index (P_s), a two-way ANOVA with precision condition (low-precision vs. high-precision) and VWM capacity (low VWM capacity vs. high VWM capacity) was also conducted. Similar to the result pattern of memory precision index, there were no significant main effects of precision condition [$F(1,24) = 0.051$, $p = .823$, $\eta^2 = 0.002$] and VWM capacity [$F(1,24) = 1.596$, $p = .219$, $\eta^2 = 0.062$]. Also, the interaction effect between the precision condition and VWM capacity was non-significant [$F(1,24) = 2.263$, $p = .146$, $\eta^2 = 0.086$].

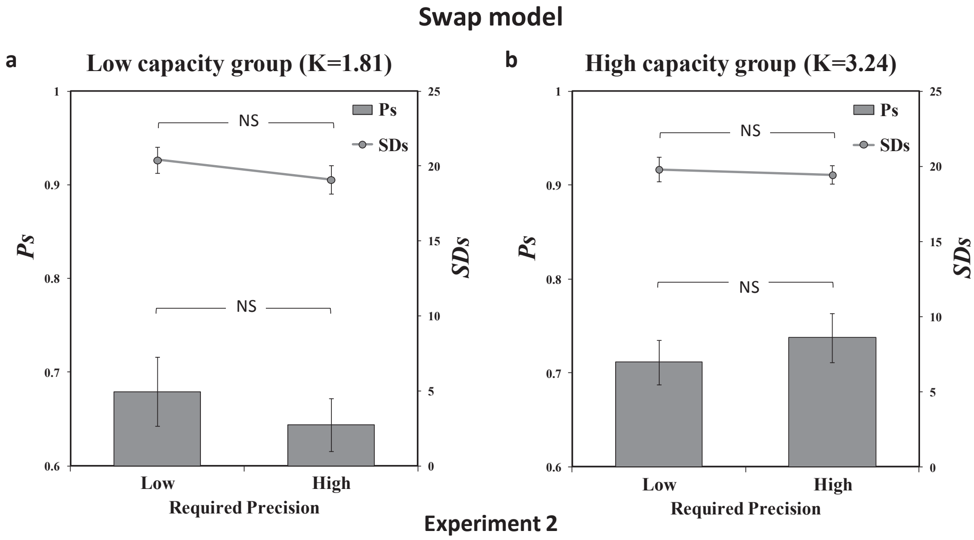

Figure 4. Swap model fitting results for the low VWM capacity group and high VWM capacity group in Experiment 2. *The graph shows the low-capacity (a) and high-capacity (b) groups' results, with the mean correct memory rate and the standard deviation presented separately for the low-precision and high-precision conditions. Error bars are standard error of the mean. NS = non-significant.*

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NEGATIVE EMOTIONAL STATE MODULATES VISUAL WORKING MEMORY IN THE LATE CONSOLIDATION PHASE

by

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Negative emotional state modulates visual working memory in the late consolidation phase

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Abstract

Although a considerable literature has grown up around the interactions between emotional state and visual working memory (VWM) performance, the mechanism underlying the impact of the negative emotional state on VWM remains unclear. The present study aimed to test whether the influence of emotional state is related to the early phase or late phase of VWM consolidation process. Across three experiments, we found that the negative emotional state did not affect VWM performance when the presentation time of stimuli was short. However, when the presentation time was long, the negative emotional state increased the VWM precision and reduced the VWM number. According to the two-phase model proposed by Ye et al. (2017), the results suggested that negative emotional state could affect the late phase of resource allocation in VWM consolidation process, but it has no impact on the early consolidation phase. The findings from this study make important contributions to the current literature regarding the emotional modulation of VWM.

Keywords: negative emotional state, visual working memory, resource allocation, two-phase model, late consolidation phase

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Introduction

Visual working memory (VWM) is a limited capacity system that can temporarily store visual information for other advanced cognitive processes (Luck & Vogel, 2013; Ma, Husain, & Bays, 2014), which provides individuals with a dynamic processing storage platform (Fukuda, Vogel, Mayr, & Awh, 2010; Ikkai, McCollough, & Vogel, 2010). Recent studies have suggested that the VWM process was influenced by the emotional state induced by negative stimuli (Figueira et al., 2017; Spachtholz, Kuhbandner, & Pekrun, 2014; Xie & Zhang, 2016). However, the impact of the negative emotional state on VWM remains unclear.

Several previous studies supported the idea that the negative emotional state would impair working memory. For example, Spies, Hesse, and Hummitzsch (1996) used classical measurements of memory span, speech rate, and reading span to show that the negative emotional state reduced working memory capacity. Figueira et al. (2017) used a change detection task to investigate the impact of the negative emotional state on VWM. By using the ERP technique and adopting a component named contralateral delay activity (CDA), which is widely held to be an indicator of VWM storage (Luria, Balaban, Awh, & Vogel, 2016; Vogel & Machizawa, 2004), Figueira et al. (2017) found that participants could store four colors in VWM under the neutral emotional state, whereas only two colors could be kept under the negative emotional state. These results have also been repeated by a follow-up study (Figueira et al., 2018). These ERP results have suggested that the negative emotional state reduces VWM capacity.

However, not all evidence supports that the negative emotional state could only reduce VWM performance. For example, by using movie clips to induce the participants' emotions, researchers found that in a change detection task both negative and positive emotion states could enhance VWM performance in the high VWM capacity group but reduce VWM performance in the low VWM capacity group (Y. Zhang, Zhang, & Liu, 2017). Thus, it may be difficult to observe the effect of emotional state on VWM performance across all participants in the change detection task. In addition, it is worth noting that there was no significant difference in the VWM behavioral performance between the neutral emotional state and negative emotional state conditions in Figueira et al. (2017)'s study. The contradiction between the ERP and behavioral results in Figueira et al. (2017) may also be attributed to the insensitivity of the behavioral index (accuracy) to the emotional state in the change detection task. The accuracy result is influenced by both the number and precision of the representations stored in VWM. Previous studies found that there was a trade-off ratio between the VWM number and precision. The number of stored items in VWM decreases with the increase of VWM precision, and vice versa (Barton, Ester, & Awh, 2009; Bays, Catalao, & Husain, 2009; Machizawa, Goh, & Driver, 2012). In this case, the adjustment in the trade-off ratio does not necessarily lead to a change of accuracy. Although the accuracy decreases with the decrease of the VWM number, it also increases with the increase of the VWM precision. Thus, if the VWM number reduces

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while the VWM precision increases, the change of the accuracy results may not be observed in the change detection task. It may explain why Figueira et al. (2017) could not find the effect of the negative emotional state on the VWM accuracy. Since the CDA component mainly reflects the number of stored representations rather than VWM precision (Gao, Yin, Xu, Shui, & Shen, 2011; but see Sessa, Luria, Gotler, Jolicoeur, & Dell'Acqua, 2011), the contradiction between the ERP and behavioral results implied that while the negative emotional state reduced VWM number, it might also improve the precision of representations in VWM. Therefore, the negative emotional state may not impair VWM, but alter the trade-off ratio between precision and number of VWM.

This possibility was supported by a previous study. By using a recall task, researchers can use a model-fitting method to separate the VWM number index and VWM precision index (W. Zhang & Luck, 2008). For instance, Spachtholz et al. (2014) investigated the impact of the negative emotional state on visual sensory memory (VSM) and VWM by using recall tasks. They found that the negative emotional state reduced the number of items stored in VSM and VWM compared with the neutral emotional state, but surprisingly, the precision of VSM and VWM increased with the decline in memory number. That is, the negative emotional state altered the trade-off ratio between precision and number in VSM and VWM. Therefore, this study provided evidence for the functional influence of the negative emotional state on VWM, which was to improve VWM precision by sacrificing the VWM number effectively.

However, even with the recall task, not all studies supported that the negative emotional state affected the trade-off ratio between precision and number in the VWM. Xie and Zhang (2016) found that the negative emotional state could improve VWM precision even without sacrificing the VWM number. That is, in their study, they only found a positive effect of the negative emotional state on VWM. Thus, although the impact of the negative emotional state on VWM remains unclear, recent studies suggest that the negative emotional state could at least increase the precision of items stored in VWM.

The processes of memory stimuli in VWM task include two important parts: sensory encoding process and consolidation process. The sensory encoding process refers to the transformation of visual information into sensory representations, while the consolidation process refers to the transformation of these sensory representations into stable VWM representations. Some researchers suggested that VWM consolidation is actually a process in which individuals allocate VWM resources[1] to their

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[1] A discrete slot-based theory (Balaban, Fukuda, & Luria, 2019; Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001; W. Zhang & Luck, 2008) and a continuous resource theory (Bays et al., 2009; Bays & Husain, 2008; Bays, Wu, & Husain, 2011; Wilken & Ma, 2004) have been proposed for the nature of mental commodity that supports VWM storage. The term *resources* used in our paper is actually a neutral term. This term has the same meaning as the term *mental commodity* in Suchow, Fougnie, Brady, and Alvarez (2014)'s study. It can either refer to the "slots" based on the framework of the discrete slot-based theory, or refer to the "continuous resources" based on the framework of the continuous resource theory. In our paper, the term *resources* is only used to improve the coherence, but it does not mean that we prefer one of these two theories.

consolidated representations (Becker, Miller, & Liu, 2013; Hao, Becker, Ye, Liu, & Liu, 2018; Liu & Becker, 2013; Mance, Becker, & Liu, 2012; Miller, Becker, & Liu, 2014). A recent proposed two-phase VWM resource allocation model has explained the resource allocation in the VWM consolidation process (Ye et al., 2017; Ye et al., 2019). The model has suggested that resource allocation is a two-phase process when individuals consolidate visual information into VWM. Since individuals are not able to anticipate the length of presentation time of external visual information in the early phase of VWM consolidation, it is conducive to their survival to maintain more visual items even with low precision. Thus, individuals would only automatically allocate VWM resources to as many representations as possible in the early phase. This leads to a fixed trade-off ratio between VWM precision and number in the early phase. That is, the trade-off ratio in the early phase is determined by the stimulus-driven factor (set size of memory stimuli). When individuals consolidate as many visual items as possible, the early phase of VWM resource allocation is completed. At this time, if the external visual information still exists, the individuals could effectively consolidate more new information into VWM for creating representations with higher precision according to their bias or strategy. For example, if the task requires participants to memorize the stimulus with high VWM precision (e.g., recall task), in the late phase of VWM consolidation participants could reduce the VWM number to free up VWM resources, and then use the resources to improve the memory precision of the remaining representations. That is, in the late phase of VWM consolidation, individuals can voluntarily reallocate VWM resources to trade off the VWM number and precision. At this phase, the trade-off ratio can be adjusted by factors other than the stimulus-driven factor. Thus, the length of presentation time of visual stimuli affects whether individuals can enter the late phase and whether they can adjust the trade-off ratio of precision and number according to their preference.

It is natural to ask about the mechanism underlying the improvement of VWM precision under the negative emotional state. There are two possibilities to explain this phenomenon. The first possibility is that the negative emotional state mainly affects resource allocation in the early phase of VWM consolidation. In the early VWM consolidation, individuals would create as many representations as possible with low precision. In the negative emotional state, individuals may consolidate the representation more effectively. For example, a negative emotional state may improve the utilization efficiency of VWM resources. The minimum memory precision of the representations formed in the early consolidation phase under a negative emotional state was higher than the one under the neutral emotional state. That is, in the negative emotional state, individuals form VWM representations with higher precision in the early consolidation phase, which leads to the enhancement of their VWM performance. The second possibility is that the negative emotional state mainly affects the voluntary VWM resource allocation in the late phase of VWM consolidation, instead of the minimum memory precision of the representations in the early consolidation phase. The precision of representation formed in the early consolidation phase under different emotional states is the same. That is, the early phase of VWM

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consolidation in different emotional states have the same effect on VWM performance. Thus, the influence of the negative emotional state on VWM performance mainly related to the later process of VWM consolidation. After individuals enter the late consolidation phase, they would reallocate VWM resources and tend to allocate more VWM resources to few representations to improve VWM precision in the negative emotional state.

Therefore, in the present study, based on the framework of the two-phase model (Ye et al., 2017; Ye et al., 2019), we tested whether the effect of negative emotional state on VWM performance related to the early phase or late phase of VWM consolidation process. If the influence of the negative emotional state on VWM performance related to the early consolidation phase and created high-precision VWM representations, it was expected that the negative emotional state could improve the VWM precision even when the presentation time of stimuli was not enough for the individuals to enter the late phase of resource allocation. On the contrary, if the influence of a negative emotional state on VWM mainly occurred in the late consolidation phase, it was expected that negative emotional state had no impact on the trade-off ratio of VWM number and precision when the presentation time was short. However, the negative emotional state did alter the trade-off ratio between VWM number and precision when the presentation time of stimuli was long enough to allow the individual to enter the late phase of resource allocation in the consolidation process.

Experiment 1

The aim of Experiment 1 was to explore the impact of the negative emotional state on the number and precision when the presentation time of stimuli was insufficient to allow participants to enter the late phase. Participants were asked to remember four orientations during 200 ms presentation time, which was too short to adjust the trade-off ratio between the VWM number and precision according to their preference (Ye et al., 2017). Thus, if the result showed that the VWM precision in the negative emotional state was higher than that in the neutral emotional state, it suggested that the negative emotional state improved the VWM precision in the early phase of the consolidation process. On the contrary, if we could not observe significant differences in VWM number and precision between the neutral and negative emotional state conditions, we would further examine the effect of negative emotional state on VWM performance in Experiment 2.

Method

Participants. Thirty-three undergraduate students from Liaoning Normal University (20 women, 33 right-handed, 19-23 years old) volunteered to participate in this experiment for compensation at a rate of $3/hour. They reported having a normal color vision and normal or corrected-to-normal visual acuity, and no history of neurological problems. Each participant provided written informed consent before the

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experiment. All procedures were conducted following the Declaration of Helsinki (2008) and were approved by the ethics committee of Liaoning Normal University (the approval number: lNNUIRB1710). Three participants were excluded due to a large guess rate (>60%), such that the results reported below were based on data from 30 participants.

We based our sample size on a previous study that compared VWM performance of neutral and negative emotion by Spachtholz et al. (2014). Based on the method proposed by Thalheimer and Cook (2002) for estimating effect sizes from t-tests, we estimated that their effect size was 0.608 for that comparison. To determine our sample size we assumed that our effect size is the same with their effect size, and calculated the sample size required to yield a power of .85 given $\alpha = .05$ for a paired-sample t-test (Faul, Erdfelder, Lang, & Buchner, 2007). This calculation showed that the minimum required sample size was 18.

Stimuli. The experiment was programmed using E-Prime 2.0. Sixty emotional images were selected from the International Affective Picture System (IAPS) for each of the two emotional state conditions (neutral and negative). Each selected image had a high agreement rate in emotion categorization. The normative valence ratings (mean [SD]) were 2.45 (0.73) for negative condition, and 5.51(0.66) for neutral condition. The normative arousal ratings were 5.75 (0.80) for the negative condition and 3.32 (0.80) for the neutral condition. T-test analyses revealed significant differences in valence, t(118) =24.02, p< .001, and arousal, t(118)= 16.62, p <.001, across these two image sets.

The memory stimuli were the same as those used in Ye et al. (2017)'s study, which were sinusoidal gratings (contrast, 0.7; spatial frequency, 3 cycles/degree) in a circular aperture (size, 0.9°) presented on a gray background. The orientation of each stimulus was randomly selected from 90 possible angles evenly spaced from 0° to 180°, with the orientations separated by at least 12°. The gratings could be presented in four possible locations located at the corners of an imaginary square (eccentricity, 3°). The experimental environment was similar to that in Ye et al. (2017)'s study, the stimuli were presented on a 19 inch CRT monitor (1280×768 pixel), and participants viewed the display at a distance of 60 cm in a dark room.

Procedure. In each trial, participants needed to complete two different tasks**.** As depicted in Figure 1, each trial started with a valence judgment task for emotion induction, followed by an orientation recall task for VWM. The valence judgment task in our study was similar to the one in Xie and Zhang (2016)'s study. An IAPS image was presented at the center of the screen for 4,000 ms, and participants reported its valence on the 9-point Self-Assessment Manikin (SAM) scale using a computer mouse. IAPS images were originally colored but were converted to gray-scale to minimize potential interference with the subsequent VWM task. The valence judgment task was followed by the orientation recall task. After an 800-ms fixation,

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four oriented gratings were presented for 200 ms, followed by a 1000 ms retention period. Then a location cue (a 1 ° square outline) appeared in one of the stimulus locations, along with an adjustable probe grating (presented at fixation). By using a computer mouse, participants adjusted the orientation of the probe to match that of the cued grating and then finalized adjustments until they were satisfied. The emotional state (negative and neutral) conditions were blocked with their order counterbalanced across participants. Each image within each condition was randomly selected and presented twice for the valence judgment task, yielding 120 trials for each condition.

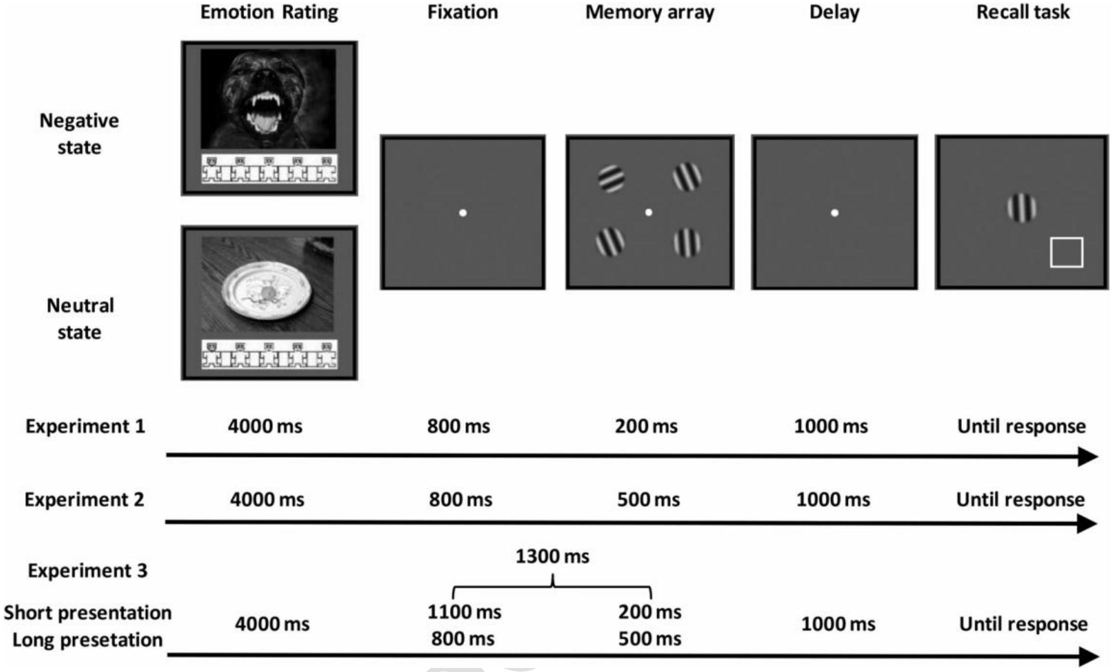

Figure 1. *Trial structure of Experiment 1, 2 and 3. A negative emotional state condition and a neutral emotional state condition with different presentation time periods of memory array (200 ms for Experiment 1; 500 ms for Experiment 2; 200 ms or 500 ms for Experiment 3) were illustrated.*

Data analysis. For each trial, the offset (error) in the recalled orientation was calculated by subtracting the reported orientation setting from the target orientation. We adopted the standard mixture model (W. Zhang & Luck, 2008) to fit the data using the MemToolbox (Suchow, Brady, Fougnie, & Alvarez, 2013). The standard mixture model assumed that performance on the orientation recall task was determined by a mixture of two types of trials. On a proportion of trials, participants did not consolidate the items into VWM but guessed, with the reported orientation conforming to a uniform random distribution. On the remaining trials, participants successfully consolidated the items into VWM, which contained a noisy representation of the target orientation, modeled by a Von Mises distribution. The model allowed us to estimate the number of items stored in VWM (K) as well as the precision of the VWM representation (SD). The K value was calculated by multiplying the set size with the probability of successful retrieval (i.e., 1- guess rate). SD was the circular standard deviation of a Von Mises distribution, which was inversely related to the VWM precision. We fitted the model to individual participant

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data in each condition and used a paired t-test to compare the model parameters at the group level to assess statistical significance between conditions (negative and neutral). In order to ensure that the chosen model can better fit the data, we compared the goodness-of-fit of the standard mixture model and the swap model by using the MemToolbox to compute the AIC (Suchow et al., 2013). The swap model assumes that besides the two types of trials in the standard mixture model, there was a third trial type in which participants reported the non-target orientation (Bays et al., 2009). The lower AICs were found for the standard mixture model, which suggested that the standard mixture model has better goodness-of-fit than the swap model. We found that the standard mixture model was most likely for 23 of 30 participants in Experiment 1, 24 of 30 participants in Experiment 2, and 23 of 30 participants in Experiment 3.

We also calculated the proportion of the experimental effect on K and SD values, assessed as $[(K_{Negative} - K_{Neutral})/K_{Average}]$ for effect on K and $[(SD_{Negative} - SD_{Neutral})/SD_{Average}]$ for effect on SD. A positive value of the experimental effect on K indicates that the proportion of negative emotional state effect can increases VWM number, while a negative value of it represents that the proportion of negative emotional state can reduce VWM number. On the contrary, a positive value of the experimental effect on SD indicates that the proportion of negative emotional state effect can decline VWM precision, while a negative value represents that the proportion of negative emotional state effect can increase VWM precision. Similar methods for calculating the experimental effects had been used in Xie and Zhang (2017)'s study.

Results and Discussion

For the pleasantness rating, the scores of the two emotional states were compared with the Wilcoxon Signed Ranks Test. The results showed that the difference between the two groups was significant, $Z = -4.412$, $p < .001$, as depicted in Figure 3a.

We fitted the mixture model to the individual participant data in each condition (Figure 2). The results showed that for both the VWM precision index (SD) and VWM number index (K), there was no significant difference in SD, $t(29)=0.339$, $p = .737$, *Cohen's d* = 0.077, and K, $t(29) = 0.702$, $p = 0.489$, *Cohen's d* = 0.116, between two conditions (Figure 3b-c).

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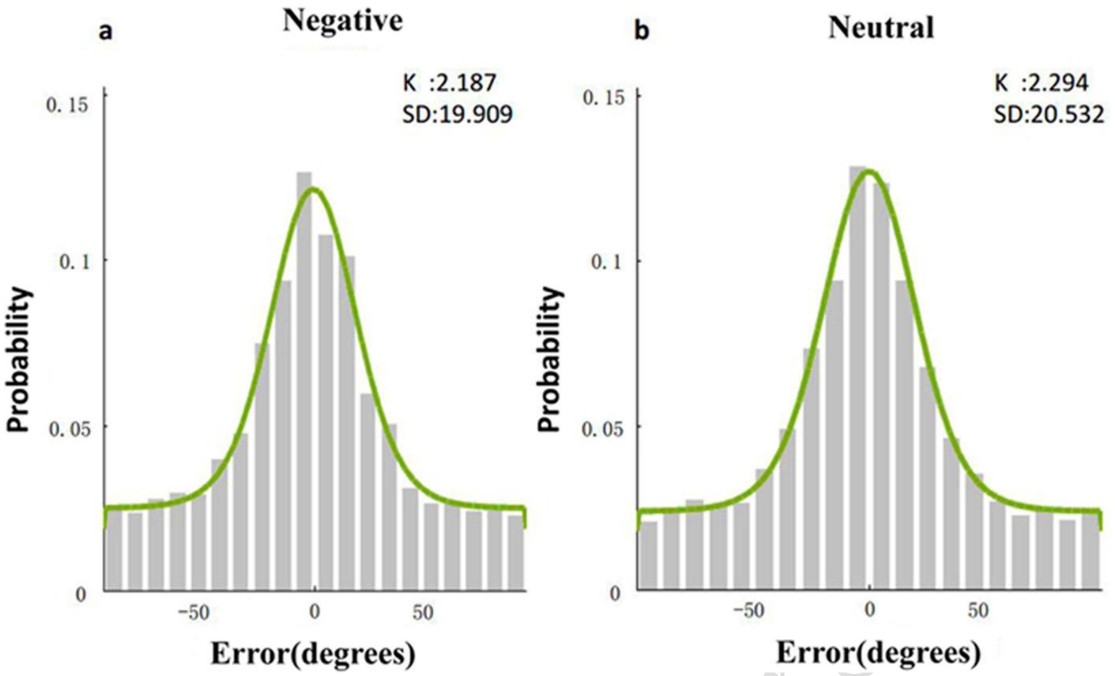

Figure 2. *Results of fitting the mixture model to the aggregate data in Experiment 1. The graphs show probability density functions for the offset of responses in the (a) negative condition, and (b) neutral condition of Experiment 1. Model fits are illustrated by continuous lines. The memory number (K) and circular standard deviation (SD) are also shown for each condition.*

For the experimental effects on SD [($SD_{Negative}$ – $SD_{Neutral}$)/$SD_{Average}$] and K [($K_{Negative}$ – $K_{Neutral}$)/$K_{Average}$], the mean experimental effects were -3.49% on K and -4.40% on SD. The effects on SD and K had no significant difference from zero, *t*(29) = 0.434, p = .667, *Cohen's d* = 0.112 (effect on SD), *t*(29) = 0.516, *p* = .610, *Cohen's d* = 0.133 (effect on K). There was no significant difference in the experimental effects on SD and K, *Z* = -0.093, *p* = .926. These results suggested that the negative emotional state had no effect on VWM precision and number.

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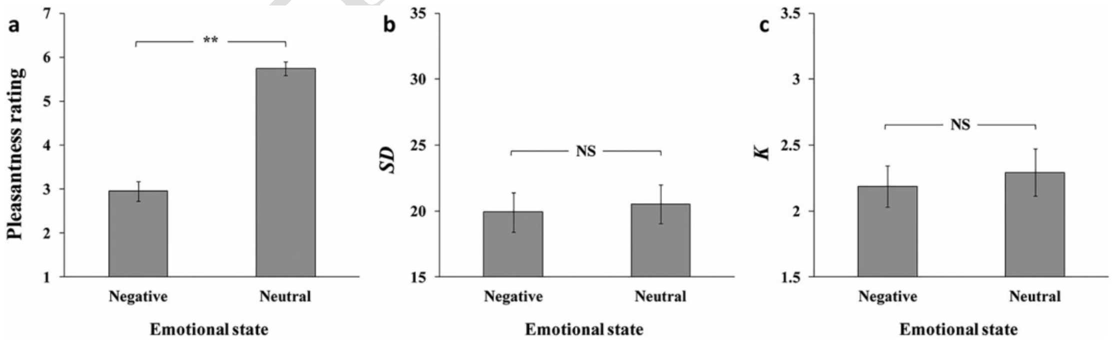

Figure 3. *The results of Experiment 1. The (a) average pleasantness ratings of the International Affective Picture System (IAPS) images, (b) SD and (c) the mean number of items stored in memory (K) are plotted separately for the negative and neutral emotional state conditions. No significant difference of SD and K was observed. Error bars are standard error of the mean. NS = non-significant; ** = p < 0.01.*

In Experiment 1, no difference was observed in VWM number and precision between different emotional state conditions. Thus, we failed to find the evidence to support that the influence of different emotional states on VWM performance was due to different early processes. There were two possibilities to explain the results. The first possibility was that, as we expected, the negative emotional state mainly actually affected the resource allocation in VWM processing. According to the study of Ye et al. (2017), the trade-off ratio between VWM number and precision only changed when the presentation time of stimuli was long enough. Previous ERP studies also showed that when the presentation time (100 to 200 ms) was short, participants could not alter the trade-off ratio between VWM number and precision according to task requirements (He, Zhang, Li, & Guo, 2015; Ye, Zhang, Liu, Li, & Liu, 2014). Thus, the presentation time in Experiment 1 might be too short to allow participants to adjust the trade-off ratio between VWM number and precision. The second possibility was that the materials used in Experiment 1 failed to induce the negative emotional state to affect VWM process. Since the null result was insufficient to reject the hypotheses, we would further test them in Experiment 2.

Experiment 2

As explained above, the two-phase model suggested that the trade-off ratio between number and precision could be adjusted when presentation time was long enough (Ye et al., 2017; Ye et al., 2019). Thus, in Experiment 2, we used the same procedure as Experiment 1 but extended the presentation time of memory stimuli from 200 ms to 500 ms, and tested whether the negative emotional state had an impact on the number and precision of VWM representations according to their preference when the presentation time was long enough.

Method

Participants. A new sample of 32 undergraduate students from Liaoning Normal University (20women, 32 right-handed,18-23 years old) volunteered to participate in this experiment for compensation at a rate of $3/hour. They reported having a normal color vision and normal or corrected-to-normal visual acuity, and no history of neurological problems. Each participant provided written informed consent before the experiment. All procedures were conducted following the Declaration of Helsinki (2008) and were approved by the ethics committee of Liaoning Normal University (the approval number: lNNUIRB1710). Two participants were excluded due to a large guess rate (>60%), such that the results reported below were based on data from 30 participants.

Stimuli, procedure, and data analysis. The design and procedure were identical to those of Experiment 1, except that we increased the presentation time from 200 ms to 500 ms, as depicted in Figure 1.

Results and Discussion

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For the pleasantness rating, the scores of the two emotional states were compared with the Wilcoxon Signed Ranks Test. The results showed that the difference between the two groups was significant, $Z = -4.782$, $p < .001$, as depicted in Figure 5a.

We fitted the mixture model to the individual participant data in each condition (Figure 4). The results showed that the VWM precision index (SD) in the negative emotional state condition was significantly lower than that in the neutral emotional state condition, $t(29) = 2.508$, $p < .05$, *Cohen's d* = 0.46, which suggested that the VWM precision in the negative condition was higher than that in the neutral condition. For the VWM number index (K), there was a significant difference between the two emotional state conditions $t(29)= 2.382$, $p < .05$, *Cohen's d* = 0.44. VWM number in the negative condition was lower than that in the neutral condition (Figure 5b-c).

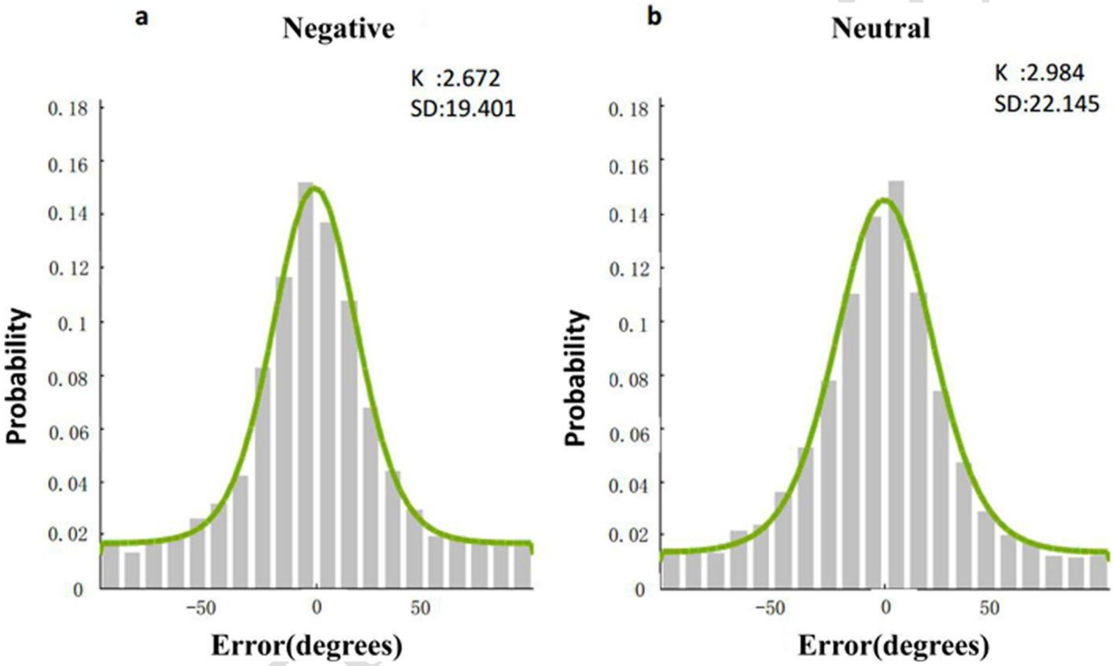

Figure 4. *Results of fitting the mixture model to the aggregate data in Experiment 2. The graphs show probability density functions for the offset of responses in the (a) negative condition, and (b) neutral condition of Experiment 2. Model fits are illustrated by continuous lines. The memory number (K) and circular standard deviation (SD) are also shown for each condition.*

For the experimental effect on SD $[(SD_{Negative} – SD_{Neutral})/SD_{Average}]$ and K $[(K_{Negative} – K_{Neutral})/K_{Average}]$, the mean experimental effect was -10.76% on SD and -12.03% on K, and both were significantly larger than zero, $t(29) = 2.413$, $p < .05$, *Cohen's d* = 0.623 (effect on K), $t(29) = 2.573$, $p < .05$, *Cohen's d* = 0.664 (effect on SD) There was no significant difference in the experimental effects on SD and K, $Z = -0.093$, $p = .926$. Unlike the results of Experiment 1, these results suggested that the negative emotional state had significant effects on VWM precision (SD) and number (K). However, the proportion of the experimental effect on VWM precision was similar to that on VWM number.

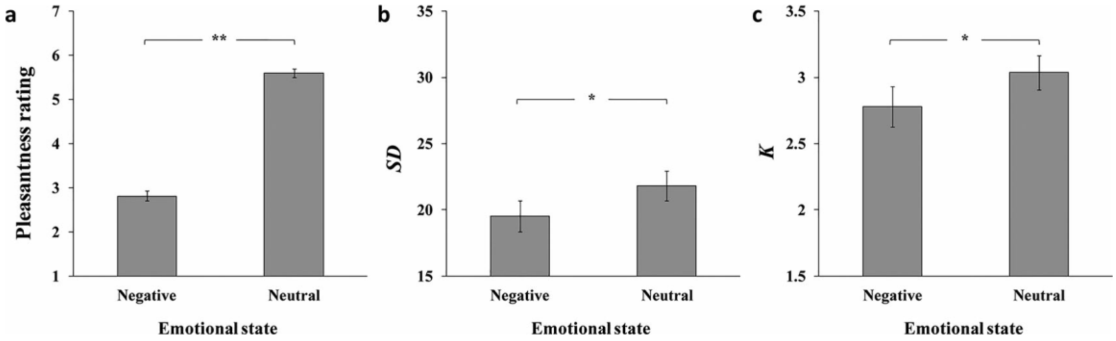

Figure 5. *The results of Experiment 2. The (a) average pleasantness ratings of the International Affective Picture System (IAPS) images, (b) SD and (c) the mean number of items stored in memory (K) are plotted separately for the negative and neutral emotional state conditions. Negative emotion improved VWM precision (i.e., smaller SD) and reduce VWM number (i.e., smaller K) Error bars are the standard errors of the means. * = p < 0.05; ** = p < 0.01.*

In Experiment 2, the results showed that when the presentation time was long, participants remembered fewer items with higher precision in the negative emotional state condition compared with the neutral emotional state condition. These results rejected the possibility that the negative emotional state induced by materials in Experiment 1 could not have an impact on the VWM performance. These results suggested that the negative emotional state affected resource allocation in the late consolidation phase when the presentation time was long.

Experiment 3

In Experiment 1 and 2, we found that a negative emotional state did not affect VWM number and precision in a short presentation time of stimuli, but when the stimuli presented for a long time, the negative emotional state made participants memorize fewer items with higher precision in VWM compared to the neutral emotional state. However, due to the contamination by two potential factors, the current evidence might be still insufficient to support that the influence of the negative emotional state on VWM representations was related to resource reallocation in the late consolidation phase.

The first potential factor was that the emotion induction degree might be different in different experiments. We knew that it took time to induce a negative emotional state. In Experiment 1, after the disappearance of emotional pictures, an 800 ms fixation screen disappeared followed by the appearance of a 200-ms memory array. In this case, the interval between the offset of emotional pictures and the offset of memory array was 1000 ms. However, in Experiment 2, after the disappearance of emotional pictures, an 800 ms fixation screen disappeared followed by the appearance of a 500-ms memory array. In this case, the interval between the offset of emotional pictures and the offset of memory array was 1300 ms. The difference between the experimental designs made it possible for the participants to consolidate the memory stimuli after the emotional pictures disappeared 1000-1300 ms only in Experiment 2.

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If the participants needed about 1000 ms to induce their negative emotional state, it would lead us to observe the effect of negative emotional state on VWM performance only in Experiment 2, but not in Experiment 1. This possibility fitted well with our current results.

The second potential factor was that there were individual differences in emotional experience between different experiments. In order to avoid the practice effect, we selected a new sample as participants in Experiment 2. This would lead to inevitable individual differences in emotional experience in different experiments. The difference in result pattern between Experiment 1 and 2 could be partly attributed to individual differences in emotional experience.

In Experiment 3, by using a within-subject design, we manipulated presentation time (200 ms and 500 ms) and emotional state (neutral and negative). Moreover, in order to ensure that the participants had the same emotional inducing time when they memorized the memory array under different presentation time conditions, we made the interval between the offset of emotional pictures and the offset of memory array consistent under different presentation conditions. These controls could eliminate potential issues in Experiment 1 and 2. In Experiment 3, we expected that we were able to observe the same findings as Experiment 1 and 2.

Method

Participants. A new sample of 35 undergraduate students from Liaoning Normal University (22 women, 34 right-handed,18-25 years old) volunteered to participate in this experiment for compensation at a rate of $5/hour. They reported having a normal color vision and normal or corrected-to-normal visual acuity, and no history of neurological problems. Each participant provided written informed consent before the experiment. All procedures were conducted following the Declaration of Helsinki (2008) and were approved by the ethics committee of Liaoning Normal University (the approval number: lNNUIRB1710). Five participants were excluded due to a large guess rate (> 60%), such that the results reported below were based on data from 30 participants.

Stimuli, procedure, and data analysis. The design and procedure were similar to those of Experiment 1 and 2, except that the same group of participants needed to complete the experiments at the presentation time of 200 ms and 500 ms. In addition, when the memory array was presented for 200 ms, the interval between the picture and the memory item was 1100 ms. When the memory item was presented for 500 ms, the interval between the picture and the memory item was still 800 ms (Figure 1). In Experiment 3, the two emotional state conditions (negative and neutral) were blocked and the order of blocks was balanced across the participants. There were 120 trials for each presentation time (200 ms and 500 ms), with a total of 240 trials per emotional state block which were fully randomized. The whole experiment included 480 trials in

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total.

Results and Discussion

For the pleasantness rating, the scores of the two emotional states were compared with the Wilcoxon Signed Ranks Test. The results showed that the difference between the two groups was significant, $Z = -4.782$, $p < .001$, as depicted in Figure 7a.

We fitted the mixture model to the individual participant data in each condition (Figure 6) and conducted an ANOVA by taking the emotional state condition (neutral emotional state vs. negative emotional state) and presentation time (200 ms vs. 500 ms) on the SD and K parameter, respectively.

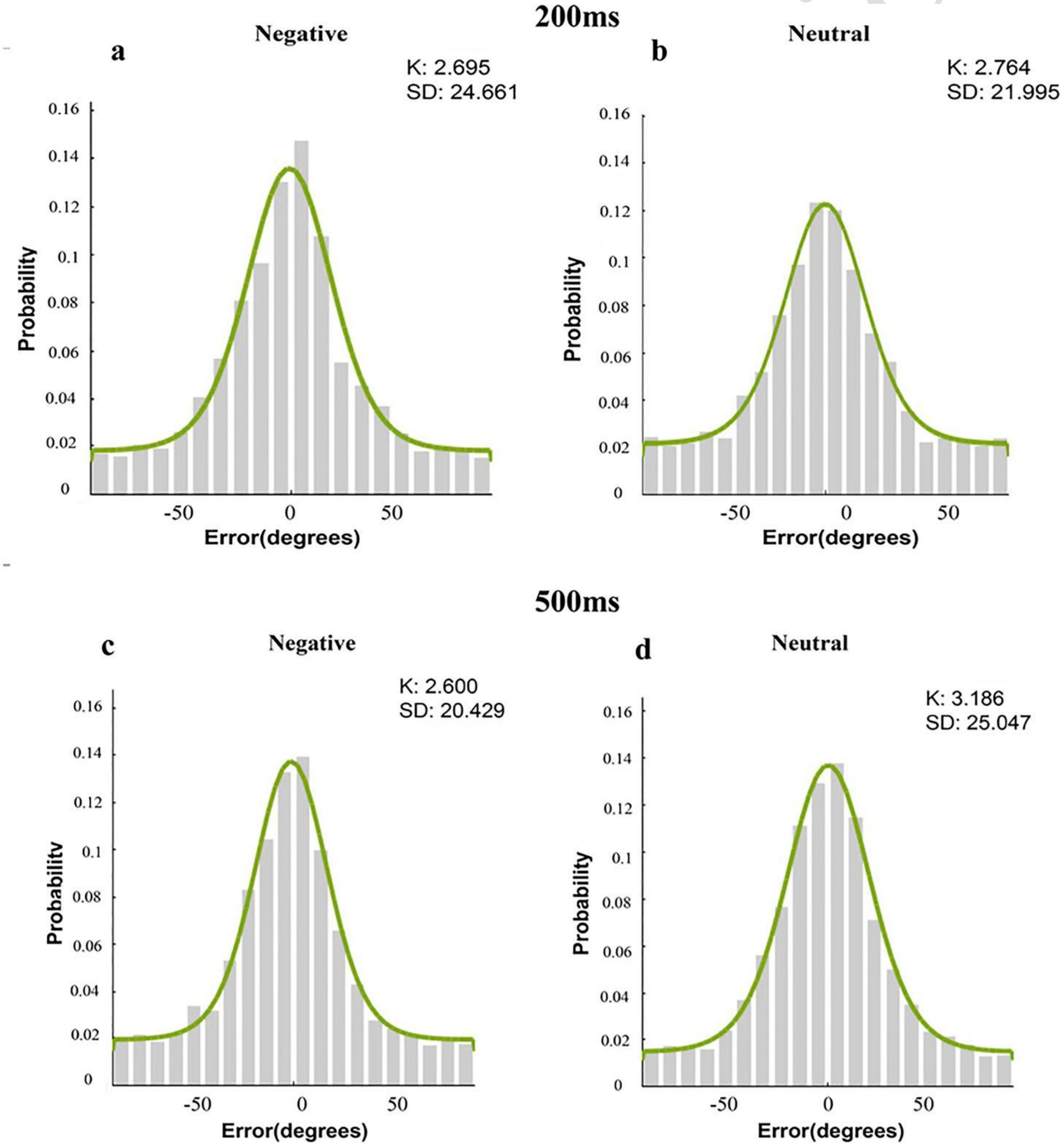

Figure 6. *Results of fitting the mixture model to the aggregate data in Experiment 3. The graphs show probability density functions for the offset of responses in the (a) negative condition, and (b)*

neutral condition when the presentation time was 200 ms. The graphs show probability density functions for the offset of responses in the (c) negative condition, and (d) neutral condition when the presentation time was 500 ms. Model fits are illustrated by continuous lines. The memory number (K) and circular standard deviation (SD) are also shown for each condition.

For SD, there was a significant interaction between emotional state and presentation time, $F(1,29) = 5.194$, $p < .05$, $\eta^2 = 0.152$, but the main effects of emotional state, $F(1,29) = 1.063$, $p = .311$, $\eta^2 = 0.035$, and presentation time, $F(1,29) = 0.167$, $p = .686$, $\eta^2 = 0.006$, were not significant. The follow-up pairwise comparison showed that when the presentation time was 200 ms, there was no significant difference in SD value between the neutral emotional state condition and negative emotional state condition, $t(29) = 0.809$, $p = .425$, *Cohen's d* = 0.154. However, when the presentation time was 500 ms, the SD value was significantly higher in the neutral emotional state condition than in the negative emotional state condition, $t(29) = 2.632$, $p < .05$, *Cohen's d* = 0.466, (Figure 7b).

For K, there was a significant main effect of emotional state, $F(1,29) = 6.269$, $p < .05$, $\eta^2 = 0.178$, and a marginally significant interaction between emotional state and presentation time, $F(1,29) = 3.371$, $p = .077$, $\eta^2 = 0.104$, but the main effect of presentation time was not significant, $F(1,29) = 1.311$, $p = .262$, $\eta^2 = 0.043$. The follow-up pairwise comparison showed that when the presentation time was 200 ms, there was no significant difference in K value between the neutral emotional state condition and negative emotional state condition, $t(29) = 0.479$, $p = .635$, *Cohen's d* = 0.105. However, when the presentation time was 500 ms, the K value was significantly higher in the neutral emotional state condition than in the negative emotional state condition, $t(29) = 3.748$, $p < .01$, *Cohen's d* = 0.670 (Figure 7c). These results were the same as those in Experiment 1 and 2.

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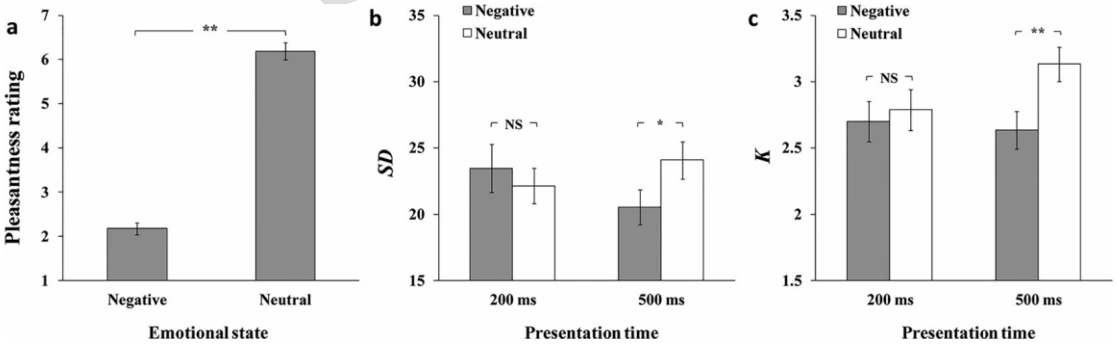

Figure 7. *The results of Experiment 3. The (a) average pleasantness ratings of the International Affective Picture System (IAPS) images, (b) SD and (c) the mean number of items stored in memory (K) are plotted separately for the negative and neutral emotional state conditions with short (200 ms) and long (500 ms) presentation time. No significant difference of SD and K was observed for short presentation time condition. In contrast, negative emotion improved VWM precision (i.e., smaller SD) and reduce VWM number (i.e., smaller K) for long presentation time condition. Error bars are standard error of the mean. * = p < 0.05; ** = p < 0.01.*

When the presentation time was 200 ms, the mean experimental effects were 1.60% on SD and -3.76% on K. The effects on SD and K showed no significant difference from zero, *t*(29) = 0.199, *p* = .844, *Cohen's d* = 0.051 (effect on SD), *t*(29) = 0.506, *p* = .617, *Cohen's d* = 0.130 (effect on K). There was no significant difference in the experimental effects on SD and K, Z = - 1.327, p = .185. When the presentation time was 500 ms, the mean experimental effects were -16.77% on SD and -18.27% on K, and both were significantly lower than zero, *t*(29) = 2.514, *p* < .05, *Cohen's d* = 0.649 (effect on SD), *t*(29) = 3.679, *p* < .01, *Cohen's d* = 0.950 (effect on K). There was no significant difference in the experimental effects on SD and K, *Z* = - 1.183, *p* = .237 (Figure 8). These results were the same as those in Experiment 1 and 2.

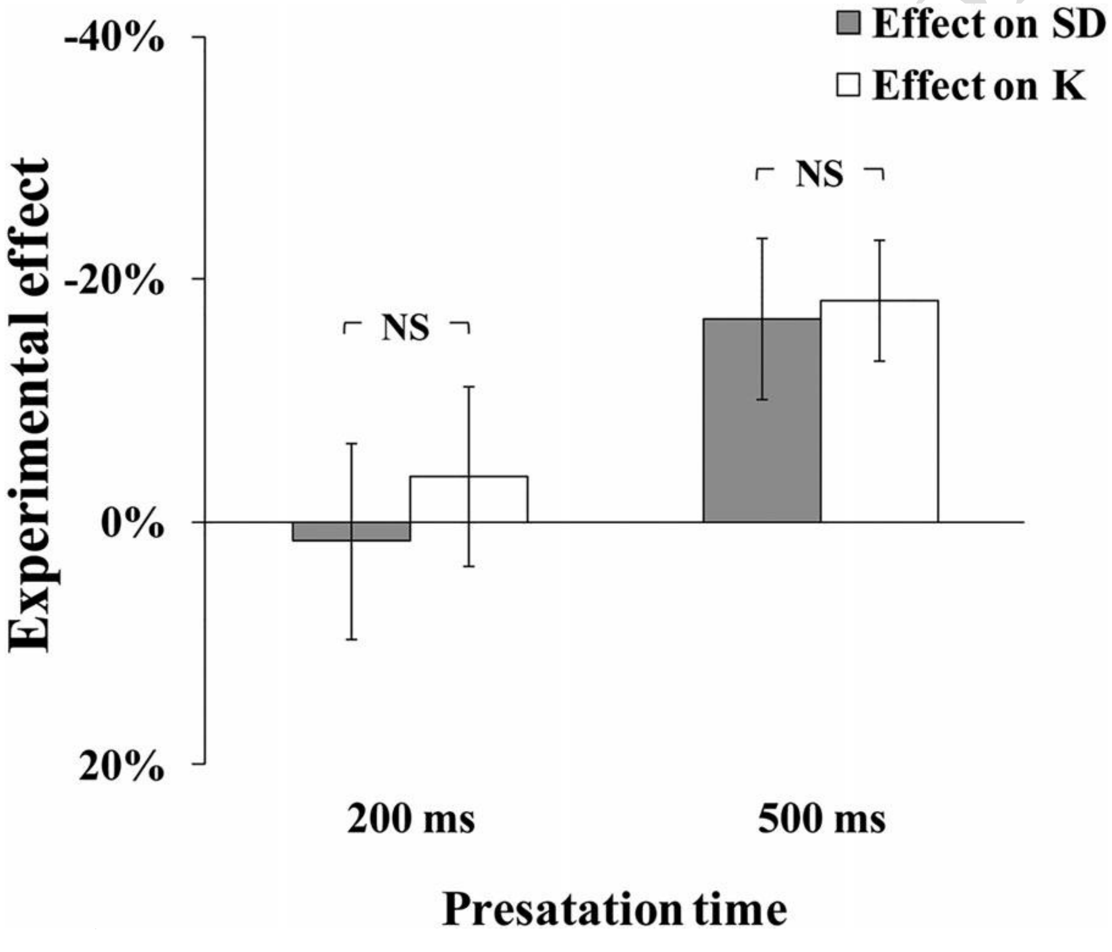

Figure 8. *The results of the experimental effect on SD [($SD_{Negative} - SD_{Neutral}$)/$SD_{Average}$] and K [($K_{Negative} - K_{Neutral}$)/$K_{Average}$] in Experiment 3. No significant difference of experimental effect was observed for both shrot and long presentation time.*

In Experiment 3, we repeated the results of Experiment 1 and 2 with a within-subject experimental design. The results rejected the possibility that the negative emotional effect shown in Experiment 2 was due to a longer time of emotion induction. In addition, Experiment 3 showed that there was no significant negative emotional effect under the short presentation time condition, while under long presentation time condition, the negative emotional state had a significant effect on the number and precision of VWM. These results supported our hypothesis that the influence of the negative emotional state on VWM representation was related to resource allocation in the late VWM consolidation phase, instead of the early process.

General discussion

The present study used recall tasks to investigate the impact of the negative emotional state on the number and precision of VWM. The results showed that the negative emotional state improved VWM precision and reduced VWM number, but this effect only occurred when the stimuli were presented for long presentation time. The negative emotional state could not affect the number and precision of VWM when the presentation time of stimuli was short. This suggested that the mechanism underlying the impact of the negative emotional state on VWM was related to the resource allocation in the late VWM consolidation phase instead of the early process.

In fact, in the field of emotion and VWM, besides the influence of the emotional state on VWM, there were also some studies which directly explored the effect of the emotional content on VWM performance (Linden, Jackson, Subramanian, Healy, & Linden, 2011; Sessa et al., 2011; Ye et al., 2018). These studies showed that participants could remember more negative emotional stimuli than neutral stimuli. This bias toward emotional stimuli may enhance the ability of emotion processing. Thus, participants could memorize more information of the negative content (e.g., angry faces) than that of the neutral content (Jackson, Linden, & Raymond, 2014; Jackson, Wu, Linden, & Raymond, 2009). However, because there are different sensory attributes between negative emotional stimuli and neutral stimuli, the studies of the effects of the emotional content on VWM would inevitably mix with the attention bias (Maljkovic & Martini, 2005). For example, negative images were more likely to attract attention than neutral images (Phelps, Ling, & Carrasco, 2006). Therefore, in order to avoid this confusion, the present study only manipulated the emotional state while keeping the memory content as the simple orientations to ensure that the influence of the emotional state on VWM was mainly related to the late phase of resource allocation in VWM consolidation, but not to the early process.

Although our study avoided the effect of memory content on VWM, our results were not entirely consistent with all previous studies on the influence of the negative emotional state on VWM. The results of our Experiment 2 and 3 suggested that when the presentation time was extended to 500 ms, the negative emotional state could lead to an increase of VWM precision and a decrease of VWM number. By calculating the experimental effects of the negative emotional state, we found that there was no significant difference in the increase of VWM precision (16.77 %) and decrease of VWM number (18.27 %) between negative and neutral emotional state conditions. That is, the negative emotional state affects both VWM precision and VWM number in the long presentation time condition. Therefore, our results supported that the

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negative emotion affected the trade-off between number and precision of VWM, rather than affecting VWM precision alone or VWM number alone. Our results were in line with the results of VWM task in Spachtholz et al. (2014)'s study, and rejected that the negative emotional state could enhance minimum memory precision of VWM representations in the early consolidation phase. However, in Xie and Zhang (2016)'s study, although there was enough presentation time of stimuli for the participants to memorize the items (400 ms for five colors in Exp 1; 1000 ms for four shapes in Exp 2), no evidence supported that the negative emotional state led to the change in trade-off ratio between the VWM number and precision. Their results only suggested that the negative emotional state could improve the VWM precision. One possible explanation for the different conclusions between their results and our results was that, in Xie and Zhang (2016)'s study (Exp 1), the number of items (five items) participants needed to remember was higher than the general VWM capacity (three to four items). A recent study found that when the number of stimuli exceeded the upper limit of individual VWM capacity, the memory performance of the individuals was worse than when they need to memorize items of a near-capacity set size (Fukuda, Mance, & Vogel, 2015). In Xie and Zhang (2016)'s study, although there was enough time to memorize the stimuli (400 ms), participants could not consolidate all stimuli into VWM because of the limitation of VWM capacity. This may lead to extra interference, which may reduce VWM number. Since the negative emotion was found to narrow attention focus (Fenske & Eastwood, 2003; Finucane, 2011), it may reduce the interference when participants consolidated the stimuli of supra-capacity set sizes. However, participants automatically traded VWM number for VWM precision in the negative emotional state. In this case, the trade-off between VWM number and precision did not necessarily lead to a change in K value. Because although the K value decreased in the trade-off, it also increased as interference decrease. Therefore, although there were significant differences in VWM precision between the different emotional state conditions, there was no difference in K value between the conditions. This possibility could also explain the result difference between Xie and Zhang (2016)'s study and Spachtholz et al. (2014)'s study. We needed to point out that our findings did not necessarily challenge the results of Xie and Zhang (2016)"s study. On the contrary, combining with the previous evidence, we proposed that the negative emotional state might have different effects on VWM performance under different memory loads. Future research could further test this hypothesis.

It is worth noting that the aim of our study was to test whether the impact of the negative emotional state on VWM was related to the early phase or late phase of VWM consolidation process. In the study of Spachtholz et al. (2014), they also examined the effect of the negative emotional state on VSM. They found that the negative emotion can also improve precision and reduced number of VSM, which suggested that negative emotion affected the sensory encoding process. At first glance, our results are in contrast to Spachtholz et al. (2014)'s study. These discrepant findings can be explained by the difference in the experimental design (memory set size) between these two studies. In their VSM task, participants needed to remember

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six items. Participants in a negative emotional state may narrow their attention focus to reduce the amount number of VSM. Therefore, in their VSM tasks, we can observe that emotion modulated memory representations even in the early sensory memory state. However, in our study, participants only needed to remember four items. The results of Experiment 1 and Experiment 3 in our study showed that negative emotional state does not modulate memory representations in the early consolidation phase or other early processes (e.g., sensory encoding process). It suggested that when the participants only need to memorize four items, even though the negative emotional state may narrow attention focus, they still have enough attention span to cover all items. Nevertheless, our study suggested that the effect of emotional state on VWM representations can be independent of the early process, but our study could not be used to reject the effect of emotional state on sensory encoding process. Especially when the encoding set size is large, the negative emotional state could have a significant impact on sensory encoding processes.

In our study, we applied bilateral recall tasks to enable participants to allocate VWM resources effectively (Y. Zhang et al., 2018). Although previous studies have found the negative emotion could lead to a narrow attention state (Finucane, 2011), their results could not reject the results of our study. The tasks in most of the studies on visual attention did not involve the processing of VWM. In the present study, we distinguished different processes based on the predictions of the two-phase model (Ye et al., 2017; Ye et al., 2019). The results showed that the negative emotional state affected the late phase of resource allocation in the consolidation process. These findings were in line with Li, Chan, and Luo (2010)'s study. They used a delayed matching-to-sample task to investigate the impact of the negative emotional state on the verbal working memory and visuospatial working memory. They found that the negative emotional state led to worse memory performance compared with the neutral emotional state. More importantly, their ERP results suggested that the difference between the negative emotional state and neutral emotional state was mainly in the VWM maintenance stage, which implied that the negative emotional state had distinct stages of influence on VWM, and there was a systematic link between specific emotions and certain cognitive processes. Future studies can investigate the effects of different emotional states on resource allocation during memory maintenance, based on VWM studies with the retro-cue (Griffin & Nobre, 2003; Landman, Spekreijse, & Lamme, 2003).

It is worth noting that the results of Experiment 3 show that especially in the neutral emotional state the longer presentation time did not lead to a substantial influence on VWM precision, even though it increased K value. This result might be due to two aspects. The first aspect was that in the neutral emotional state the VWM capacity limitation of most participants would be reached when four orientation are memorized. Thus, participants would memorize the items as many as possible with the lowest precision. The second aspect was that the consolidation of orientation is a serial consolidation process (Becker et al., 2013; Hao et al., 2018; Liu & Becker, 2013;

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Miller et al., 2014). The consolidation speed of participants was about 100 ms/item (Vogel, Woodman, & Luck, 2006). Thus, in the short presentation time condition, the number of items consolidated should be less than the upper limit of their VWM capacity. In contrast, in the long presentation time condition, the number of items consolidated would reach the upper limit. However, no matter in short or long presentation time conditions, participants would store items with the same minimum precision. In the neutral emotional state, participants would not sacrifice VWM number to improve VWM precision. Therefore, the VWM number increased with the presentation time but the VWM precision remains the same in the neutral emotional state.

It is natural to ask whether different emotional states really modulate VWM resource allocation or manipulate the generic task strategies of participants under different emotional conditions (e.g., strategically trade quantity for quality only in the negative emotional condition). By mixing different emotional conditions in each block, Experiment 2 in Xie and Zhang (2016)'s study provided evidence that the effect of emotional modulation was not due to the difference in generic task strategy. Moreover, in Experiment 3, we mixed different presentation time conditions in each emotional block. We found that there were differences in trade-off patterns under different presentation time conditions in the same emotional block. More importantly, participants who used different generic task strategies under different emotional conditions had no obvious benefit. The difference in generic task strategy under different emotional blocks seems difficult to explain these results. It is possible that the trade-off of precision and capacity was based on automatic resource allocation (i.e., cognitive process bias). When individuals are able to reallocate VWM resource (at the late phase of VWM resource allocation), they may have an involuntary bias to trade quantity for quality under the negative emotional state. This involuntary bias for quality might have evolved because of the need to maintain more detailed information to deal with potential dangers that often arise in negative situations. Previous studies could support this idea. For example, Sessa et al. (2011)'s study has shown that the VWM precision of fearful face is higher than that of the neutral face.

A recent study has shown that in the recall task, the response data may show categorical response biases (Hardman, Vergauwe, & Ricker, 2017). Thus, it is possible that the difference of trade-off patterns between VWM precision and number in different emotional states was due to the effect of negative emotional state on categorical response biases. That is, the emotional state modulates the tendency to make a response based on categorical information. However, this possibility could not explain why the negative emotional state could not affect the trade-off in the short presentation time (200 ms) condition. In addition, we checked our dataset by visual observation. The only interesting thing was that when the participants made a guess response (reported angle and actual angle were very different), they may choose a 90-degree angle, but they would choose less near 90 degrees (e.g., 85-89 degree or 91-95 degree). This may be because the 90-degree angle (vertical angle) was the

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default value in our experiments. When participants decided to choose a vertical angle to make a guess response, they were not willing to make further adjustments to the angle. However, this phenomenon existed in both neutral and negative emotional state conditions (in both short and long presentation time conditions). Therefore, although our participants may have a certain bias (especially for vertical angles) in response, this might not be the main reason to cause the difference between different emotional state conditions in our study.

In our study, as Ye et al. (2017)'s study, we used 200 ms and 500 ms presentation time (without a post-mask) to distinguish different presentation time conditions. Previous studies found that, because of retinal persistence, visual information persistence can exist 100 ms to 500 ms after stimulus disappeared (Averbach & Coriell, 1961; Brockmole, Wang, & Irwin, 2002; Coltheart, 1980; Di Lollo & Dixon, 1988). It seems to suggest that there is little difference between different presentation time conditions. However, it may not be the case. After the memory items disappear, individuals could use the retinal persistence to consolidate representations, but when they needed to improve memory precision through consolidation, it mainly relies on the period when the external stimulus still exists, instead of the total time when visual information of retinal persistence exists. This was because only when the external stimulus still exists can individuals extract more detailed information from the external visual stimulus for consolidation to improve the precision of VWM representation. Once the visual stimulus disappears, although the visual information could still exist on the retina for a period of time, the visual information fades rapidly during this period, which makes it difficult for consolidation to use the visual information of retinal persistence to improve VWM precision. Therefore, the visual information of retinal persistence does not weaken the effect of stimulus presentation time on VWM representations. Although some early studies on VWM consolidation mainly used fixed presentation time of memory array and manipulated the memory-and-mask ISI (Vogel et al., 2006; W. Zhang & Luck, 2008), recent studies on VWM consolidation had begun to directly manipulate the presentation time of memory array with no memory-and-mask ISI (Becker et al., 2013; Hao et al., 2018; Liu & Becker, 2013; Mance et al., 2012; Miller et al., 2014; Rideaux, Apthorp, & Edwards, 2015; Rideaux & Edwards, 2016). Therefore, in our study, the presentation time of memory array not only limits the encoding process, but also limits the time that participants can improve memory precision in VWM consolidation. However, because different researchers may have some subtle differences in the definition of VWM consolidation, this may lead to uncertainty in the relationship between presentation time manipulation and VWM consolidation. In particular, the presentation time may have an impact on some processing (e.g., eye-movement, mind wandering) other than VWM. Future studies need to pay attention to the influence of these other time-related factors on the results when researchers control the presentation time of memory array.

Recently, Xie and Zhang (2017) found that negative emotions improved not only the

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VWM precision but also the precision of visual long-term memory (VLM). The mechanism underlying the impact of the negative emotional state on VLM may be different from that of the negative emotion on VWM. Future studies can compare the effects of negative emotion on VWM and VLM to investigate the effects of emotional states on memory mechanisms. In addition, the research on the effect of emotional state on VWM can not be limited to memory storage. For example, by using a retro-cue that points to an object (Griffin & Nobre, 2003; Landman et al., 2003) or a dimension (Niklaus, Nobre, & van Ede, 2017; Ye, Hu, Ristaniemi, Gendron, & Liu, 2016), previous studies found that attention can be directed to information in VWM and improve the VWM performance. This phenomenon is called the retro-cue effect in VWM. Future studies can examine the effect of different emotional states on the retro-cue effect.

It is also worth noting that there might be some model fitting artifacts in our results due to a limited number of trials per condition. Therefore, although our study proposed a new perspective to reconcile the conflicting findings of previous relevant studies (Spachtholz et al., 2014; Xie & Zhang, 2016), the conclusion needs to be further confirmed in future studies. Moreover, our results have provided new evidence for the effect of emotional state at the behavioral level. Future studies need to leverage converging evidence from both behavioral and neural data (e.g., EEG, MEG) to better articulate this issue.

In summary, our study found that the effect of negative emotional state on the trade-off between quantity and quality of VWM may only occur under the condition with a long presentation time of the memory stimuli. These results suggested that the emotional modulation of VWM mainly related to the late phase of VWM resource allocation in the consolidation process, instead of in the early consolidation phase. By affecting the late phase of VWM resource allocation, the negative emotional state could improve VWM precision by sacrificing VWM number. The findings from this study make important contributions to the current literature regarding the emotional modulation of VWM.

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Acknowledgments

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Author Contributions Statement

F. L., Q. L., and C. Y. conceived and designed the experiments. F. L., performed the data acquisition and analyzed the data. Q. L., C.Y., and F. L. interpreted the data. C. Y., F. L., and Q. L. drafted the manuscript. All authors revised and approved the manuscript.

Conflict of interest

The authors have declared that no competing financial and/or non-financial interests exist.

Data availability statement

The datasets generated during and/or analysed during the current study are available from the corresponding author (lq780614@163.com, Qiang Liu) on reasonable request.

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III

THE IMPACT OF VISUAL WORKING MEMORY CAPACITY ON THE FILTERING EFFICIENCY OF EMOTIONAL FACE DISTRACTORS

by

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The impact of visual working memory capacity on the filtering efficiency of emotional face distractors

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ABSTRACT

Emotional faces can serve as distractors for visual working memory (VWM) tasks. An event-related potential called contralateral delay activity (CDA) can measure the filtering efficiency of face distractors. Previous studies have investigated the influence of VWM capacity on filtering efficiency of simple neutral distractors but not of face distractors. We measured the CDA indicative of emotional face filtering during a VWM task related to facial identity. VWM capacity was measured in a separate colour change detection task, and participants were divided to high- and low-capacity groups. The high-capacity group was able to filter out distractors similarly irrespective of its facial emotion. In contrast, the low-capacity group failed in filtering the neutral and angry face distractors, while the filtering was efficient for the happy face distractors. The results indicate that potentially threatening faces are particularly difficult to filter if VWM capacity is limited.

1. Introduction

Humans must maintain visual contents in a temporary storage buffer in order to allow for their effective processing. This mental storage system is called visual working memory (VWM). VWM allows integration of information from sensory inputs, thus enabling a dynamic and coherent visual experience. VWM representations can be mentally accessed and manipulated, even when the visual scene disappears (Cowan, 2001; Luck & Vogel, 1997). Moreover, relevant information from a visual scene can be selected by VWM for processing, and distracting information can be filtered (Vogel, McCollough, & Machizawa, 2005).

Of all the different kinds of visual information, humans are most specialised at perception of faces, and faces capture attention more efficiently than other meaningful objects (Ro, Russell, & Lavie, 2001; Vuilleumier, 2000; Young & Burton, 2018). There are different processing advantages for different emotional faces; for example, angry faces are particularly efficient at capturing our attention (Fox et al., 2000; Hansen & Hansen, 1988; Pinkham, Griffin, Baron, Sasson, & Gur, 2010). Studies of VWM have also shown that emotional expressions modulate performance of face identification. Data from behavioural studies indicated that participants could store more facial identities in VWM when the faces were angry than when they were happy or neutral, even if the facial emotions were irrelevant to the task (Jackson, Wu, Linden, & Raymond, 2009; Jackson, Linden, & Raymond, 2014). These results suggest that, compared to happy and neutral faces, angry faces can enhance storage of visual information for facial identities. However, in behavioural studies, VWM storage is difficult to study without involvement of other cognitive processes, such as memory encoding and decision-making.

In the present study, VWM for emotional faces was investigated by using a recently found event-related potential (ERP) component called contralateral delay activity (CDA; also known as sustained posterior contralateral negativity, or SPCN) which can index the number of objects maintained by VWM. Its amplitude is strongly modulated by the number of items in VWM during the maintenance phase (Feldmann-Wüstefeld, Vogel, & Awh, 2018; Gao et al., 2009, 2011; Vogel & Machizawa, 2004), and it reaches an asymptote once approximately three to four simple objects are stored, reflecting the limitation of individual's VWM capacity (Luria, Balaban, Awh, & Vogel, 2016). CDA has been used to index VWM storage of facial objects (Meconi, Luria, & Sessa, 2014; Sessa & Dalmaso, 2016; Sessa, Luria, Gotler, Jolicoeur, & Dell'Acqua, 2011; Sessa et al., 2012). Sessa et al. (2011) used CDA to investigate the VWM maintenance of fearful faces. Participants were

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asked to memorise identities of fearful or neutral faces. Their results showed that memorising the identity of a fearful face elicited larger CDA amplitude than that of a neutral face (Sessa et al., 2011). The authors suggested that participants maintained more visual information in the VWM for fearful faces compared to neutral faces.

Recently, studies on VWM for emotional faces have expanded from maintenance to distractor filtering (Stout, Shackman, & Larson, 2013; Stout, Shackman, Johnson, & Larson, 2015). Researchers have used CDA to investigate filtering efficiency of irrelevant information during VWM processing (Stout et al., 2013; Vogel et al., 2005). Stout et al. (2013) used this method to study efficiency of filtering task-irrelevant fearful faces. Participants were asked to memorise the identity of one neutral target face while ignoring a distractor (either a fearful or a neutral face). CDA amplitude was larger for the fearful distractor condition compared to the condition without a distractor (one-target condition). However, CDA amplitude did not differ between the neutral distractor condition and one-target condition (Stout et al., 2013). The results thus indicate that fearful distractors are automatically stored in VWM, even when they are irrelevant to the task, while neutral distractors are effectively filtered out of VWM. This suggests that the type of distractor itself affects filtering efficiency. Quite surprisingly, previous studies have not used CDA to investigate filtering efficiency of VWM for faces other than fearful or neutral.

Filtering efficiency of distractors is also affected by an individual's VWM capacity (Jost, Bryck, Vogel, & Mayr, 2011; Owens, Koster, & Derakshan, 2012; Vogel et al., 2005). Vogel et al. (2005) found that individuals with high and low VWM capacity differ in their efficiency at filtering irrelevant objects during VWM tasks. Participants were instructed to memorise two targets' orientations and ignore two distractors' orientations. CDA amplitude was used to examine whether irrelevant distractors unnecessarily consume VWM storage. The result suggested that participants with high VWM capacity were able to filter out the distractors, but those with low VWM capacity tended to store distractors to VWM. Cowan and Morey (2006) interpreted this result as showing that VWM depends on attentional filtering. Because VWM and selective attention share some similar neural mechanisms (Ku, 2018), this could explain why VWM capacity and filtering efficiency are interlinked. Further support has been provided by a study which showed that high-capacity individuals were more capable of resisting attentional capture than low-capacity individuals (Fukuda & Vogel, 2009).

However, although many previous studies have investigated the influence of VWM capacity on filtering efficiency of simple neutral distractor items (colours or orientations as target features, Owens et al., 2012; Vogel et al., 2005), very little is known about the impact of VWM capacity on filtering efficiency of emotional face distractors. The purpose of the present study is to provide first-hand evidence on the impact of VWM capacity on ability to filter emotional face distractors.

Because the focus of the present study is on VWM filtering efficiency rather than on maintenance efficiency, a low memory load similar to the study by Stout et al. (2013) was chosen. Participants were asked to selectively remember the identities of one or two faces while ignoring others. Angry and happy faces were used as emotional distractors because these have not been applied in previous CDA studies (Meconi et al., 2014; Sessa & Dalmaso, 2016; Sessa et al., 2011, 2012; Stout et al., 2013). There were three categories of conditions in this study: one-target condition (one neutral face), two-target conditions (two neutral faces, or one neutral and one emotional face) and distractor conditions (one neutral target face and one neutral distractor face, or one neutral target face and one emotional distractor face).

Based on previous CDA studies (Vogel & Machizawa, 2004; Vogel et al., 2005), it was predicted that CDA amplitude in two-target conditions would be larger than that in the one-target condition, and CDA amplitude in distractor conditions would be between those in one-target and two-target conditions. In principle, if participants could filter out the distractors, then CDA amplitude of distractor conditions would not be different from that of one-target condition. On the contrary, if they could not filter out the distractors, then there would be no difference in CDA amplitude between distractor and two-target conditions.

The study by Vogel et al. (2005) suggested that individuals with low VWM capacity are less efficient at filtering out simple neutral distractors. Although the results related to filtering of simple neutral distractors may not necessarily be generalised to filtering of neutral face distractors, it was hypothesised that participants with low VWM capacity would be less efficient at filtering neutral face distractors than high-capacity participants.

Furthermore, because several studies have proposed that angry faces can automatically capture more attention compared to happy faces (Fox et al., 2000; Hansen & Hansen, 1988; Pinkham et al., 2010), it was hypothesised that filtering of angry face distractors would be more difficult than filtering of happy face distractors. This might be especially true for low-capacity participants because they can be assumed to be worse at resisting attentional capture by distractors (Fukuda & Vogel, 2009).

2. Method

2.1. Participants

As paid volunteers, forty-two undergraduate students (21.65 ± 2.07 years old, age range 18–25 years; 2 left-handed; 10 males) were recruited from the volunteering participant pool at Liaoning Normal University in China. The inclusion criteria for participants were age of 18 years or more, self-reported normal colour vision and normal or corrected-to-normal visual acuity. Exclusion criteria were history of psychiatric disorders and previous participation in working memory experiments. Written informed consent was provided by each participant prior to the experiment. All procedures were in compliance with the Declaration of Helsinki and were approved by the ethics committee of Liaoning Normal University.

2.2. Tasks

The study consisted of two tasks: a facial VWM task followed by a VWM capacity measurement. To investigate the VWM processing of facial objects, electroencephalography (EEG) measurements with responses time-locked to the stimuli were applied while the participants conducted the facial VWM task. A colour change detection task was used as the VWM capacity measurement to quantify capacity in each participant. In order to ensure the ERP results of the facial VWM task would not be influenced by the experience of VWM capacity measurements, participants first completed the facial VWM task and then the VWM capacity measurement after a short break. Participants were seated in a sound-proof dark room at a distance of 70 cm from a 17-inch screen.

2.3. Materials

In the facial VWM task, three different types of emotional (neutral, angry and happy) facial images were used as stimuli. A previous study suggested that participants have an advantage when detecting angry expressions on male faces compared to female faces (Becker, Kenrick, Neuberg, Blackwell, & Smith, 2007). To maximise the effects of attentional capture by angry faces, only pictures of male actors were used in the experiment. A total of 54 images of male faces (18 neutral, 18 angry and 18 happy) were selected from the Chinese Facial Affective Picture System (CFAPS; Gong, Huang, Wang, & Luo, 2011). The CFAPS has been widely used to investigate human emotional face processing (Guo et al., 2013; Liu, Zhang, & Luo, 2014; Luo, Feng, He, Wang, & Luo, 2010; Tian et al., 2018; Zheng et al., 2015). In the CFAPS, all images are similar in size, background, spatial frequency, contrast grade, brightness and other physical properties. Each selected image had a high agreement rate in emotion categorisation (more than 70% agreement rate for each angry and neutral expression image and more than 90% agreement rate for each happy expression image). One-way ANOVAs were used to investigate whether valence and arousal differed between the categories of emotional faces. There was a main effect for both valence, $F(2,51) = 216.348$, $p < 0.001$ and arousal $F(2,51) = 14.307$, $p < 0.001$. Follow-up pairwise comparisons showed that the valence of neutral faces ($M = 4.19$, $SD = 0.65$) was significantly more positive than that of angry faces ($M = 2.66$, $SD = 0.39$; $p < .001$) and more negative than that of happy faces ($M = 6.48$, $SD = 0.59$; $p < .001$). The arousal of neutral faces ($M = 4.44$, $SD = 0.46$) was significantly lower than that of angry ($M = 6.31$, $SD = 1.35$; $p < .001$) and happy faces ($M = 5.80$, $SD = 1.22$; $p < .001$), but there was no significant difference in arousal between angry and happy faces ($p = .280$).

Faces were presented with a grey background and were framed with rectangular borders (2.6° wide × 3° tall). Both the memory array and test array contained facial images that were placed in fixed locations surrounding a fixation cross. Horizontal distance between the facial images and the fixation cross was 2.9°. Vertical distance between the top and bottom of faces was 1.6°.

In the VWM capacity measurement, all stimulus arrays were presented with a grey background, and they occupied a $9.8^{\circ} \times 7.3^{\circ}$ area (Fig. 2). Each item in the stimulus array was a square (size: $0.65^{\circ} \times 0.65^{\circ}$), the colour of which was selected at random without replacement from a set of seven discriminable colours (red, green, blue, orange, yellow, purple, pink). The positions of squares were randomised on each trial and were separated by at least 2°.

2.4. Experimental procedure

2.4.1. Facial VWM task

The basic trial structure was a facial lateralised change detection task adapted from the study by Stout et al. (2013). Because the consolidation of VWM representation is a coarse-to-fine process (Gao & Bentin, 2011; Gao, Ding, Yang, Liang, & Shui, 2013), relatively long exposure duration (500 ms) was used to ensure that participants could voluntarily allocate VWM resource to remember details (Ye et al., 2017). The trial structures are depicted in Fig. 1a. Each trial began with a fixation cross (500 ms in duration) in the centre of the screen, followed by a pair of arrow cues (200 ms), which were displayed above and below the fixation cross, both pointing to the same direction (either to left or right). After a variable interval (200–400 ms), a memory array of two or four faces was displayed (500 ms). Following the memory array, a blank screen (900 ms) preceded the onset of the test array. The test array was exposed until participants responded. Participants were instructed to maintain fixation throughout the trial and were asked to only memorise the identity of the faces in the visual hemifield as indicated by the cues. The faces presented in the non-cued visual hemifield always maintained the same emotion as the ones in the cued hemifield. The faces were surrounded by red or yellow frames (target or distractor frames, counterbalanced across participants). Participants were asked to only memorise the identity of faces surrounded by the target frames and indicate by a button press whether there was a change in the target identity or not. Participants were explicitly informed that the emotion of the faces and the faces displayed in the non-cued visual hemifield were irrelevant for the task. The test array in the cued visual hemifield had one different face than the memory array in 50% of the trials; they were identical in the remaining trials. When a change in identity of a target occurred, the facial emotion remained the same. The change did not occur on the distractor faces or the faces in the non-cued visual hemifield. The participant's task was to indicate whether the test array was identical to the memory array or if a target face had changed identity. Instruction emphasised response accuracy rather than response speed. Following the response, a variable interval (900–1100 ms) elapsed before the beginning of the next trial.

Examples of memory array of cued visual hemifield in each condition can be found in Fig. 1b. The task included three categories of conditions: one-target condition, two-target conditions and distractor conditions. The 1 neutral target (1Nt) condition served as the baseline. Three different two-target conditions were applied in which the set size was two and only task-relevant faces were presented. The combinations were 2 neutral targets (2Nt), 1 neutral target and 1 angry target (1Nt1At) or 1 neutral target and 1 happy target (1Nt1Ht). In addition, to assess the impact of facial distractors on VWM maintenance, three different distractor conditions, neutral, angry and happy, were applied. The combinations were 1 neutral target and 1 neutral distractor (1Nt1Nd), 1 neutral target and 1 angry distractor (1Nt1Ad) or 1 neutral target and 1 happy distractor (1Nt1Hd). Consequently, there were a total of seven conditions in the facial VWM task. Participants completed 160 trials for each condition, with a total of 1120 trials organised into eight 140-trial blocks which were fully randomised. There was a 30-s break between each 140-trial block. At least 24 practice trials were given prior to recording test performance. The entire task lasted approximately 75 min.

2.4.2. VWM capacity measurement

As a conventional paradigm, the single-probed colour change detection paradigm was used in the VWM capacity measurement (Vogel et al., 2005). The paradigm was first introduced by Phillips (1974) and popularised by Luck and Vogel (1997). As illustrated by Fig. 2, each trial began with a fixation cross (500 ms), which was followed by a sample array of six coloured squares (200 ms). Participants were instructed to remember these coloured squares. After a blank interval (900 ms), a probe array with 1 coloured square (2500 ms) was presented. The task was to indicate whether the probe coloured was the same as the one in that specific location in the memory array, with accuracy rather than response speed being stressed. The colours within a given array were selected at random without replacement from the chosen colours. All participants completed 100 trials of this task, with a 30-s break after first 50 trials. The measurement lasted approximately 10 min.

2.5. EEG recording and analysis

During the facial VWM task, EEG activity was recorded continuously using a 64-channel elastic cap. In addition to the online vertex (Cz) reference, the data were algebraically re-referenced off-line to the average of the left and right mastoids during post-recording analyses. The vertical electro-oculogram (VEOG) was recorded with a pair of bipolar-referenced electrodes, one above and one below the right eye. The horizontal electro-oculogram (HEOG) was recorded with a pair of bipolar-referenced electrodes placed laterally to the outer canthi of both eyes. Impedance at each electrode site was maintained below 5 kΩ. The EEG and EOG signals were amplified with a 50 Hz low-pass and were digitised at a sampling rate of 500 Hz.

The EEG was segmented into 1600 ms epochs starting from 200 ms before the onset of the memory array. The averaged ERP waveforms were filtered by applying a 17 Hz low-pass filter (Ye, Zhang, Liu, Li, & Liu, 2014). Epochs were baseline corrected for the 200 ms pre-stimulus interval. The trials contaminated with horizontal eye movements and reflected as HEOG amplitude greater than ± 70 μV were excluded from analysis. After that, trials with remaining artefacts exceeding ± 80 μV in amplitude were rejected. Participants with trial rejection rates higher than 30% were excluded from the analyses. Ten participants (all right-handed; one male) were excluded on this basis. The results reported here are thus based on data from the remaining 32 participants. The number of excluded participants was similar to previous ERP studies (Sessa et al., 2011; Stout et al., 2013).

3. Statistical analysis

A significance level of $p < .05$ was used for all tests. Also, marginally significant ($p < .10$) results were reported. Mixed-model

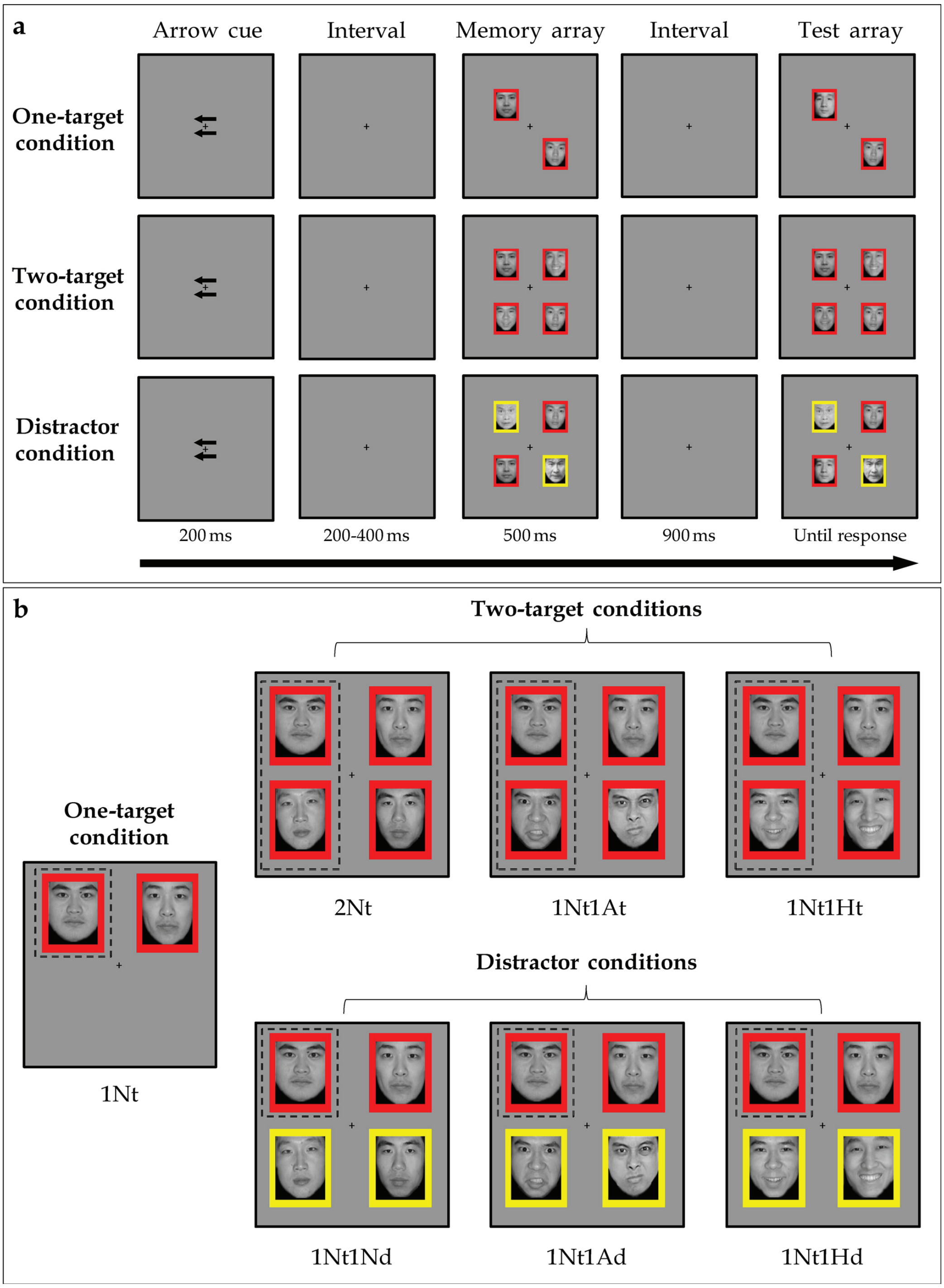

Fig. 1. a) Trial structure of the VWM task and three categories of conditions. All arrow cues point to the left visual hemifield, red frame indicates targets to be memorised and yellow frame indicates distractors. Here only trials with identity changes are demonstrated. b) One example of memory array for each of seven different conditions in the trial, with arrow cues pointing to the left visual hemifield. The dashed line is used to indicate target items and was not present during the experiment (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

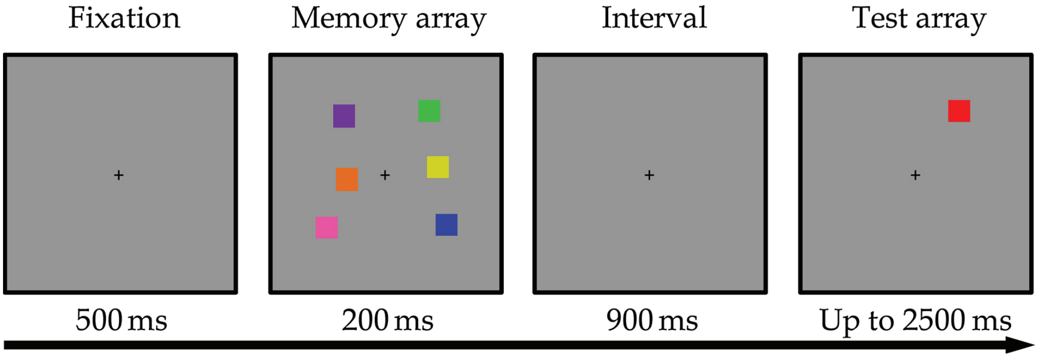

Fig. 2. The trial structure of the VWM capacity measurement (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.).

repeated measures ANOVA with conditions (1Nt vs. 1Nt1Nd vs. 1Nt1Ad vs. 1Nt1Hd vs. 2Nt vs. 1Nt1At vs. 1Nt1Ht) as a within-subject factor and VWM capacity group (high-capacity vs. low-capacity) as a between-subject factor were conducted for behavioural accuracy and CDA amplitude. The paired t-tests were conducted for the follow-up pairwise comparison of different emotional conditions (neutral, angry and happy) in both groups with a bootstrapping method (SPSS version 24.0; 10,000 permutations with 95% confidence intervals). Cohen's *d* was used as an estimator of the effect size for the t-tests. Two-tailed t-tests were conducted for the behavioural results. Due to a clear prediction of the difference direction in CDA amplitudes, one-tailed t-tests were conducted for these. Bayes factor analysis was used to avoid null results that were observed by chance (Rouder, Speckman, Sun, Morey, & Iverson, 2009). Bayes factor (BF_{10}) provides an odds ratio for the alternative/null hypotheses (values < 1 favour the null hypothesis and values > 1 favour the alternative hypothesis). For example, a BF_{10} of 0.25 would indicate that the null hypothesis is 4 times more likely than the alternative hypothesis.

3.1. *ERP data analysis*

Based on previous studies (He, Zhang, Li, & Guo, 2015; McCollough, Machizawa, & Vogel, 2007; Shen, Yu, Xu, & Gao, 2013), four pairs of electrodes at posterior parietal sites (P5/6, PO3/4, PO5/6, PO7/8) were chosen for analysis. For each stimulus condition, the contralateral waveforms were calculated by averaging the activity recorded at left hemisphere electrode sites when participants were cued to memorise the right side of the memory array, and with the activity recorded at right hemisphere electrode sites when they were cued to memorise the left side. The ipsilateral waveforms were computed by averaging left and right hemisphere sites when participants were cued to memorise the left and right side of the memory array, respectively. The CDA amplitude was defined by subtracting the ipsilateral activity from the contralateral activity, with a measurement window of 550–1000 ms after the onset of the memory array. Instead of choosing the time window from 500 ms, selecting this time period allowed for avoiding possible contaminations due to perceptual processing since it is successive to the disappearance of the memory array.

3.2. *VWM capacity measurement analysis*

Similar to studies reporting individual differences in VWM capacity (Fukuda, Vogel, Mayr, & Awh, 2010; Fukuda, Mance, & Vogel, 2015; Gaspar, Christie, Prime, Jolicoeur, & McDonald, 2016; Matsuyoshi, Osaka, & Osaka, 2014), VWM capacity of each participant was quantified based on their results in the colour change detection task. The standard formula proposed by Cowan (2001) was applied: $K_c = N (H - F)$, where K_c is VWM capacity, N is the size of the array (i.e. six in the present study), H is the hit rate or proportion of correct responses when a change is present and F is the false alarm rate or proportion of incorrect responses when no change is present. As with many previous VWM studies, participants were divided into a high-capacity group and a low-capacity group by using a median split on their K_c scores (Li, He, Wang, Hu, & Guo, 2017; Owens et al., 2012; Vogel et al., 2005; Weaver, Hickey, & van Zoest, 2017; Zhou et al., 2011).

4. Results and discussion

The median split on the K_c scores resulted in 16 participants (1 left-handed; 5 males) in the high-capacity group (M = 2.70, SD = 0.54) and 16 participants (1 left-handed; 4 males) in the low-capacity group (M = 1.54, SD = 0.34). VWM capacity differed between the groups ($p < .001$). The sample set size in each capacity group was similar to a previous study using a similar split into low- and high-capacity groups (Owens et al., 2012). No difference was found in the number of valid trials between the high- (M = 78.30%, SD = 8.76%) and low-capacity (M = 79.57%, SD = 9.40%) groups. A mixed-model repeated measures ANOVA with conditions (1Nt vs. 1Nt1Nd vs. 1Nt1Ad vs. 1Nt1Hd vs. 2Nt vs. 1Nt1At vs. 1Nt1Ht) and VWM capacity group (high-capacity vs. low-capacity) found no significant effects on the number of valid trials (all *p*-values > 0.154).

4.1. *Behavioural results*

The accuracies in each stimulus condition for the high- and low-capacity groups are shown in Fig. 3a and b and reported in Table 1. The ANOVA showed significant main effects of condition, F(6,180) = 125.031, $p < .001$, $\eta^2 = 0.806$, and of VWM capacity group, F(1,30) = 4.797, $p < .05$, $\eta^2 = 0.179$, but no significant interaction between condition by group, F(6,180) = 1.828, $p = .152$, $\eta^2 = 0.057$. The accuracy of the high-capacity group (M = 0.79, SD = 0.107) was better than that of the low-capacity group (M = 0.72, SD = 0.128). The accuracy was higher in the conditions in which participants needed to memorise one target (1Nt, 1Nt1Nd, 1Nt1Ad and 1Nt1Hd) than two targets (2Nt, 1Nt1At and 1Nt1Ht; all *p*-values < .001). There was no significant difference in accuracy between 1Nt, 1Nt1Nd, 1Nt1Ad and 1Nt1Hd conditions (all *p*-values > .452). Similarly, there was no significant difference between 2Nt, 1Nt1At and 1Nt1Ht conditions (all *p*-values > .308). The results showed that memory accuracy was worse for two-target than for one-target and distractor conditions. Although the participants with high VWM capacity had better performance than the participants with low VWM capacity, the groups did not differ in their performance as a function of condition.

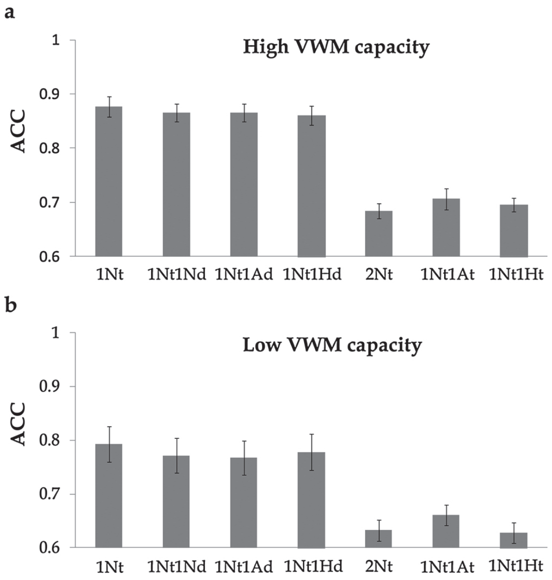

Fig. 3. Accuracy in high-capacity group (a) and low-capacity group (b) separately in each condition. Mean values with error bars show standard error of mean.

Table 1
Mean values and standard deviation (in parentheses) for behavioural accuracy and CDA amplitude in each condition.

Condition	High VWM capacity		Low VWM capacity	
	Accuracy	CDA amplitude	Accuracy	CDA amplitude
1Nt	0.88	−1.10	0.79	−0.93
	(0.07)	(0.98)	(0.13)	(1.18)
1Nt1Nd	0.87	−1.26	0.77	−1.40
	(0.07)	(1.04)	(0.13)	(0.88)
2Nt	0.68	−1.95	0.63	−1.44
	(0.06)	(1.11)	(0.08)	(0.82)
1Nt1Ad	0.87	−1.23	0.77	−1.45
	(0.07)	(0.88)	(0.13)	(1.34)
1Nt1At	0.71	−2.12	0.66	−1.61
	(0.08)	(1.22)	(0.08)	(1.02)
1Nt1Hd	0.86	−1.28	0.78	−0.79
	(0.07)	(1.08)	(0.13)	(1.29)
1Nt1Ht	0.70	−1.88	0.63	−1.42
	(0.05)	(1.09)	(0.08)	(1.00)

4.2. ERP results

The CDA amplitudes in different conditions for the high- and low-capacity groups are presented in Table 1. The ANOVA showed a significant main effect of condition, F(6,180) = 10.038, $p < .001$, $\eta^2 = 0.251$, and a significant interaction effect of condition by group, F(6,180) = 2.400, $p < .05$, $\eta^2 = 0.074$, but no significant main effect of VWM capacity group, F(1,30) = 0.604, $p = .443$, $\eta^2 = 0.020$. Unlike the behavioural results, the CDA results showed that CDA amplitude in different conditions is modulated by the VWM capacity group. The different patterns in behavioural and ERP results may be due to the fact that CDA can index mere VWM maintenance phase.

Follow-up pairwise comparison to investigate the effects of different emotions in target faces on the VWM maintenance of facial identity was conducted. CDA amplitude was compared across the one-target, distractor and two-target conditions for each emotion (1Nt vs. 1Nt1Nd vs. 2Nt for neutral emotion; 1Nt vs. 1Nt1Ad vs. 1Nt1At for angry emotion; 1Nt vs. 1Nt1Hd vs. 1Nt1Ht for happy emotion).

4.2.1. CDA amplitude in neutral conditions

Fig. 4 illustrates CDA amplitude and grand-averaged CDA waveform in neutral conditions (1Nt, 1Nt1Nd and 2Nt conditions) separately for high- and low-capacity groups.

Results showed that in the high-capacity group, the CDA amplitude in 2Nt condition was larger than both 1Nt (t[15] = 4.006, $p < .001$, CI$_{95\%}$[0.48, 1.29], $d = 0.81$, $BF_{10} = 67.98$) and 1Nt1Nd (t[15] = 3.341, $p < .01$, CI$_{95\%}$[0.30, 1.09], $d = 0.66$, $BF_{10} = 21.32$) conditions, but there was no difference between 1Nt and 1Nt1Nd conditions (t[15] = 0.858, $p = .199$, CI$_{95\%}$[−0.53, 0.20], $d = 0.16$, $BF_{10} = 0.55$). In the low-capacity group, the CDA amplitudes in both 1Nt1Nd (t[15] = 2.459, $p < .05$, CI$_{95\%}$[−0.86, −0.11], $d = 0.46$, $BF_{10} = 4.86$) and 2Nt (t[15] = 2.521, $p < .05$, CI$_{95\%}$[0.10, 0.90], $d = 0.51$, $BF_{10} = 5.36$) conditions were larger than 1Nt condition, but there was no difference between 2Nt and 1Nt1Nd conditions (t[15] = 0.303, $p = .384$, CI$_{95\%}$[−0.20, 0.29], $d = 0.04$, $BF_{10} = 0.33$).

As expected, these results suggest that the neutral face distractors could be filtered by participants with high VWM capacity, but participants with lower VWM capacity had lower filtering efficiency. The results for filtering neutral facial distractors were consistent with previous results for filtering simple neutral distractors (Jost et al., 2011; Owens et al., 2012; Vogel et al., 2005).

4.2.2. CDA amplitude in angry conditions

Fig. 5 illustrates the CDA amplitude and grand-averaged CDA waveform for the angry conditions (1Nt1Ad and 1Nt1At conditions) in comparison to 1Nt condition separately for the high- and low-capacity groups.

The results showed that, in the high-capacity group, CDA amplitude in 1Nt1At condition was larger than in both 1Nt (t[15] = 4.069, $p < .001$, CI$_{95\%}$[-1.52, -0.56], $d = 0.92$, $BF_{10} = 75.98$) and 1Nt1Ad (t[15] = 4.562, $p < .001$, CI$_{95\%}$[0.50, 1.28], $d = 0.84$, $BF_{10} = 179.22$) conditions, but there was no difference between the 1Nt and 1Nt1Ad conditions (t[15] = 0.765, $p = .228$, CI$_{95\%}$[-0.44, 0.20], $d = 0.13$, $BF_{10} = 0.50$). In the low-capacity group, CDA amplitude in 1Nt1At was significantly larger than in 1Nt condition (t[15] = 3.692, $p < .001$, CI$_{95\%}$[−1.07, −0.35], $d = 0.62$, $BF_{10} = 39.25$), but it was not different between 1Nt1At and 1Nt1Ad conditions (t[15] = 0.600, $p = .280$, CI$_{95\%}$[−0.36, 0.68], $d = 0.14$, $BF_{10} = 0.43$). CDA amplitude was marginally larger in 1Nt1Ad condition than in 1Nt condition (t[15] = 1.635, $p = .063$, CI$_{95\%}$[−1.16, 0.08], $d = 0.42$, $BF_{10} = 1.42$). The pattern of results for angry face conditions was similar to that of neutral face conditions. The high-capacity group efficiently filtered the angry distractors, while the low-capacity group stored angry face distractors to VWM. The result was in line with the hypothesis.

4.2.3. CDA amplitude in happy conditions

Fig. 6 illustrates CDA amplitude and grand-averaged CDA waveforms for happy conditions (1Nt1Hd and 1Nt1Ht conditions) in comparison to 1Nt condition separately for the high- and low-capacity groups.

The results showed that, in the high VWM capacity group, CDA amplitude in 1Nt1Ht condition was larger than in both 1Nt (t[15] = 4.375, $p < .001$, CI$_{95\%}$[-1.14, -0.44], $d = 0.75$, $BF_{10} = 129.59$) and 1Nt1Hd (t[15] = 5.181, $p < .001$, CI$_{95\%}$[0.38, 0.82], $d = 0.55$, $BF_{10} = 517.35$) conditions, but there was no difference between 1Nt and 1Nt1Hd conditions (t[15] = 0.930, $p = .185$, CI$_{95\%}$[-0.56, 0.19], $d = 0.18$, $BF_{10} = 0.60$. Similar to the high-capacity group, in the low-capacity group, CDA amplitude in the 1Nt1Ht condition was significantly larger than both in 1Nt1Hd (t[15] = 2.238, $p < .05$, CI$_{95\%}$[0.15, 1.23], $d = 0.54$, $BF_{10} = 3.43$) and in 1Nt (t[15] = 1.906, $p < .05$, CI$_{95\%}$[−0.98, −0.01], $d = 0.45$, $BF_{10} = 2.08$) conditions, but it was not different between 1Nt and 1Nt1Hd conditions (t[15] = 0.903, $p = .808$, CI$_{95\%}$[−0.16, 0.43], $d = 0.11$, $BF_{10} = 0.15$).

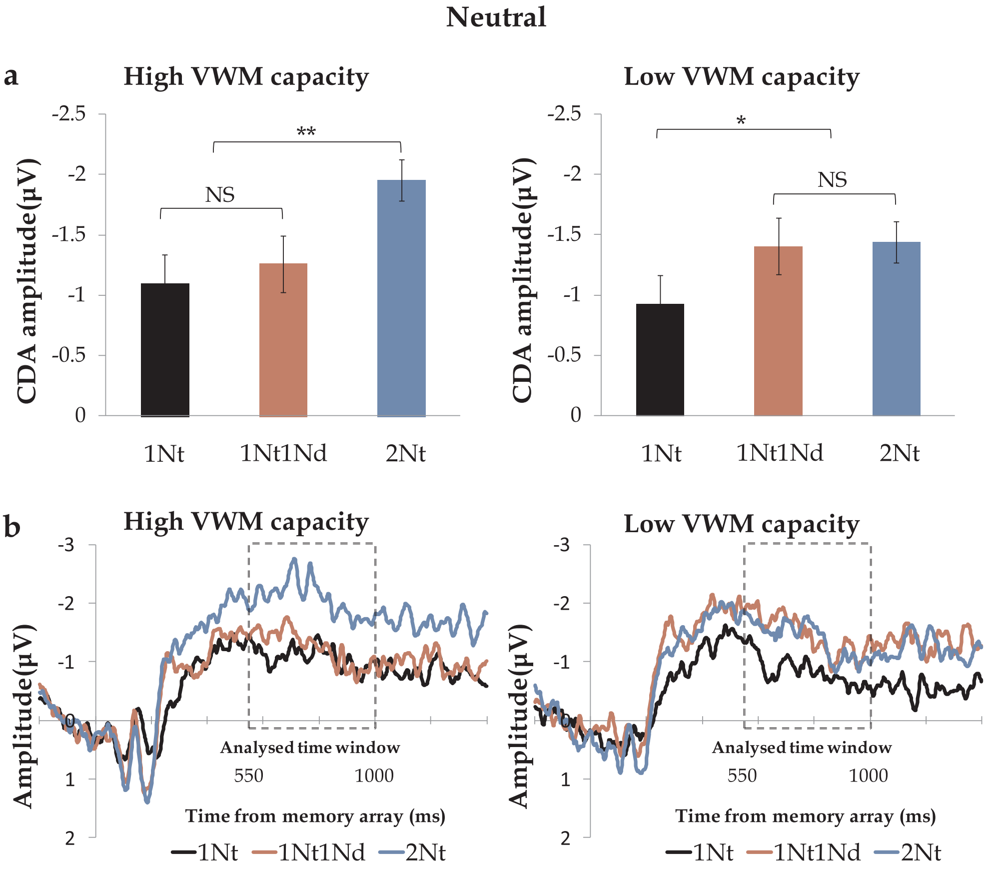

Fig. 4. a) The results of the CDA amplitude for the high (left) and low (right) VWM capacity groups in neutral conditions. Mean amplitude values and their error bars show the standard error of mean. NS = non-significant; * = $p < 0.05$; ** = $p < 0.01$. b) Grand-averaged ERP waveforms time-locked to the onset of the memory array in different conditions for the high (left) and low (right) VWM capacity groups. CDA was analysed from the area marked with the rectangle.

Interestingly, the results showed a different pattern for happy conditions compared to neutral and angry conditions. Both the high- and low-capacity groups were able to effectively filter happy face distractors. In addition, CDA amplitude increased from one target to two targets. Previous research has established that CDA amplitude reflects the number of items held in VWM, and it increases with set size and reaches an asymptotic level when the set size reaches the storage limitation (Luria et al., 2016; Vogel & Machizawa, 2004). Given the property of CDA, it can be inferred that both the high- and low-capacity groups could store one neutral face and one happy face at the same time. These results are necessary to ensure that effective filtering of happy face distractors is not due to insufficient storage space for distractors.

5. General discussion

The main goal of the present study was to investigate the impact of VWM capacity on the filtering efficiency of emotional face distractors. It was found that the influence of VWM capacity was different for filtering different emotional faces. The individuals with high VWM capacity were able to filter all emotional faces. However, the individuals who had low VWM capacity had difficulties in filtering both angry and neutral faces but succeeded in filtering happy faces.

The results related to filtering of neutral faces mirrored the previous results of filtering simple neutral objects (Vogel et al., 2005). Both in this study, conducted with face stimuli, and in the study by Vogel et al. (2005), where non-face objects were applied, participants with high VWM capacity could filter out task-irrelevant objects, but participants with low VWM capacity maintained information about the task-irrelevant objects. This implies that the filtering mechanism for simple neutral objects (e.g. orientations or colours) could be generalised to the filtering mechanism for complex neutral objects (e.g. faces).

Quite surprisingly, the individuals with high VWM capacity were able to filter out all distractors, including the threat-related distractors (angry faces). Previous studies have shown that fearful distractors are more difficult to filter than neutral ones (Stout et al., 2013). The discrepancy between these results related to angry faces, and those related to fearful faces by Stout et al. (2013) may be due to the differences in the neural mechanisms recruited by angry and fearful faces (Fitzgerald, Angstadt, Jelsone, Nathan, & Phan, 2006; Whalen et al., 1998). Although angry faces can capture attention effectively (Fox et al., 2000; Hansen & Hansen, 1988; Pinkham et al., 2010), participants with high VWM capacity seem to have a strong ability to resist attention capture, and therefore they could filter out angry face distractors. However, as expected, the low-capacity participants had difficulties filtering angry faces. This result is in line with a previous study, which reported that participants with high VWM capacity were better at resisting attentional capture by distractor objects than those participants who had lower VWM capacity (Fukuda & Vogel, 2009).

Interestingly, participants in the low-capacity group were able to

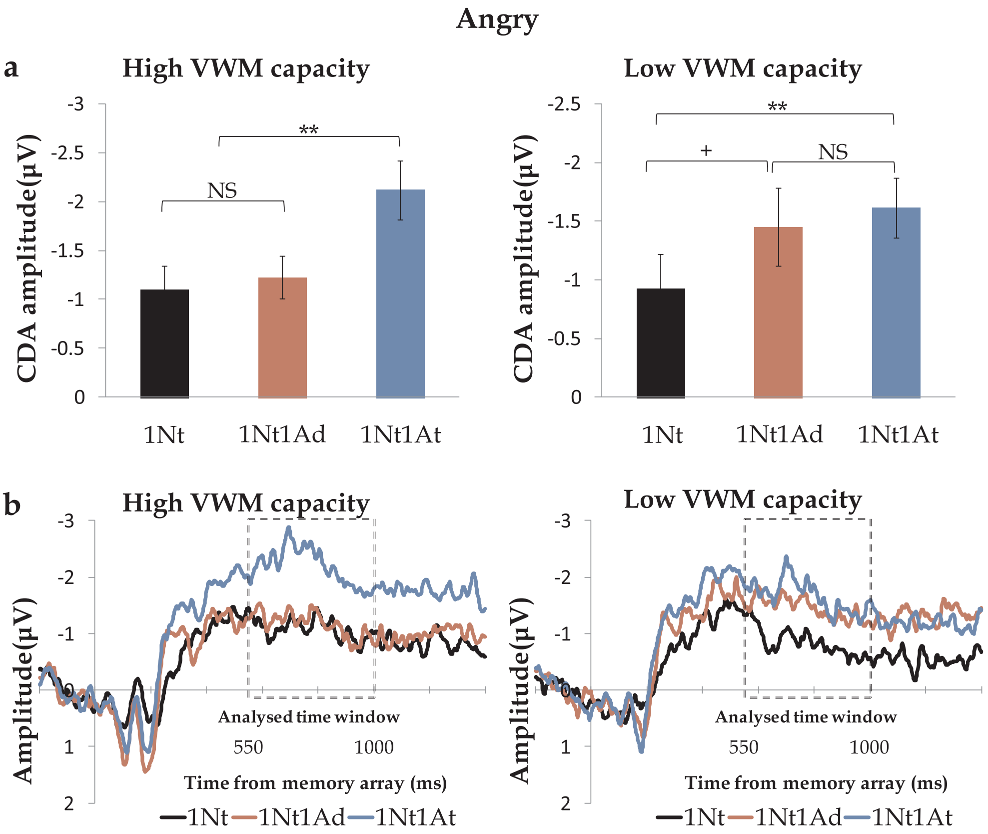

Fig. 5. a) The results of the CDA amplitude for the high (left) and low (right) VWM capacity groups in the one-target condition and angry conditions. Mean amplitude values and their error bars show the standard error of mean. NS = non-significant; + = $p < 0.1$; ** = $p < 0.01$. b) Grand-averaged ERP waveforms time-locked to the onset of the memory array in different conditions for the high (left) and low (right) VWM capacity groups. CDA was analysed from the area marked with the rectangle.

effectively filter happy face distractors. It thus seems to be that individuals with low VWM capacity have different filtering efficiencies for different emotional faces, since they were not able to filter neutral and angry distractors. One recent study may help in explaining why this is so. By using a directed forgetting paradigm, Tay and Yang (2017) found that angry faces were much more resistant to intentional forgetting than happy faces, suggesting that angry faces are better than happy faces at being retained in memory, despite participants' considerable effort to forget. Thus, it can be speculated that the low-capacity individuals may have consolidated the happy face distractors into VWM as they did for angry and neutral distractors, but they could quickly forget the happy distractors during VWM maintenance. Tay and Yang (2017) interpreted their above-mentioned results as related to attentional bias toward angry faces and cognitive resources devoted to them. This is a logical explanation in the context of these results as well. The involuntarily bias for potentially threatening expressions might have evolved because of the need to maintain more visual information to deal with potential sources of danger (e.g. potentially threatening persons). The individuals who had low VWM capacity had difficulties in filtering both angry and neutral faces. It is possible that neutral faces attracted attention as potentially threatening expressions. Happy faces, on the other hand, are more easily evaluated as non-threatening (Nummenmaa & Calvo, 2015).

There are some potential limitations in this study. As demonstrated by Stout et al. (2013), healthy participants with elevated anxiety allocated unnecessary VWM resources to fearful faces when they were irrelevant to the task at hand. Furthermore, anxiety is associated with poorer working memory capacity (Moran, 2016). Although the participants in the current study reported no current or previous psychiatric diagnoses, neither questionnaires (e.g. the State-Trait Anxiety Inventory) nor clinical interviews were used to measure anxiety. This can be seen as a potential limitation of this study. However, we have no reason to believe that the participants had elevated amount of anxiety.

Another limitation of the study is that, in order to ensure that there were equal numbers of participants in both VWM capacity groups, participants were divided into the two groups using a median split on their K_c scores, as done in several previous studies (Li et al., 2017; Owens et al., 2012; Vogel et al., 2005; Weaver et al., 2017; Zhou et al., 2011). This resulted in the VWM capacity of some participants in the two groups to be close to the median K_c, and might lead to an underestimation of the between-subject differences. In future researches on different VWM capacity groups, it would be better to first measure VWM capacity for a large sample and then choose the study sample from the two ends of the distribution to form the high- and low-capacity groups.

In summary, this study demonstrates different patterns of filtering efficiency for different emotional face distractors in individuals with high and low VWM capacity for neutral objects. Low VWM capacity seems to make the filtering of potentially threatening information (neutral and angry faces) particularly difficult. Although the results are

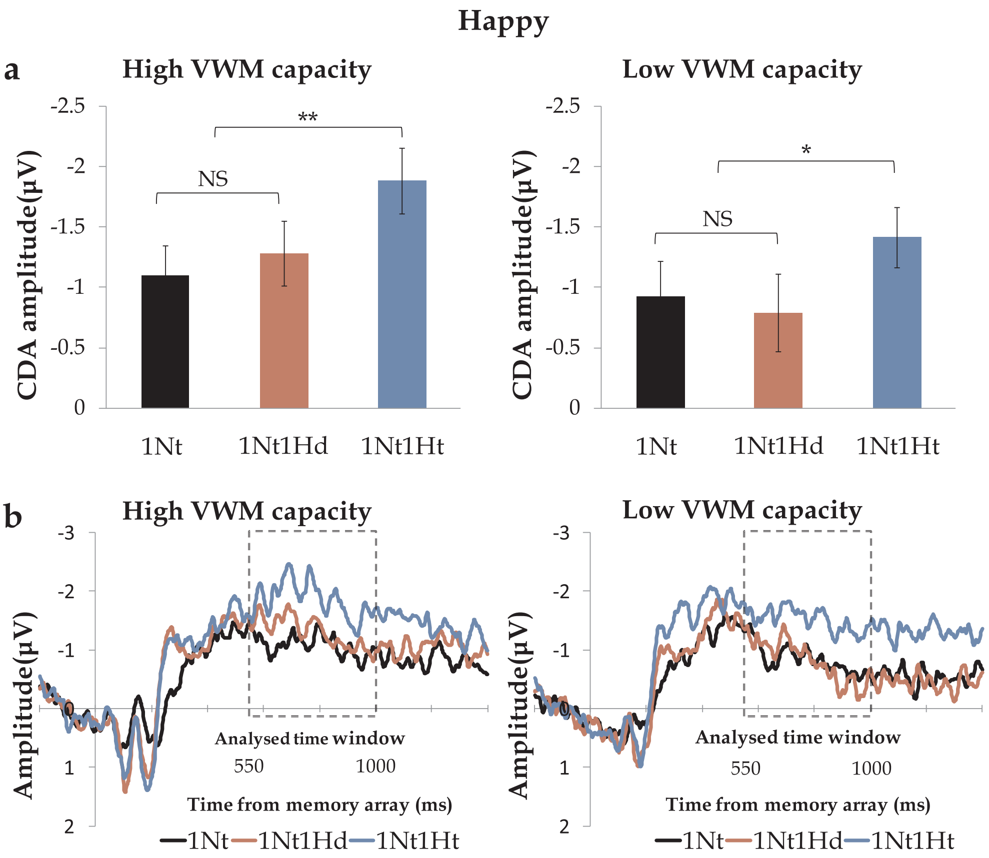

Fig. 6. a) The results of the CDA amplitude for the high (left) and low (right) VWM capacity groups in the one-target condition and happy conditions. Mean amplitude values and their error bars show the standard error of the mean. NS = non-significant; * = $p < 0.05$; ** = $p < 0.01$. b) Grand-averaged ERP waveforms time-locked to the onset of the memory array in different conditions for the high (left) and low (right) VWM capacity groups. CDA was analysed from the area marked with the rectangle.

obtained in an experimental condition, VWM capacity could influence tasks that require use of VWM to remember new people in real-life social situations.

Author contributions statement

QL and CY conceived and designed the experiment. QX performed the experiment. CY, QX and FC analysed the data. CY, PA, QL and QX wrote the main manuscript text. PS and TR improved the manuscript.

Conflict of interest

The authors have declared that no competing interests exist.

Data statement

The datasets generated and analysed during the present study are available from the corresponding author on reasonable request.

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IV

EFFICIENT FILTERING OF SAD AND FEARFUL FACES FROM WORKING MEMORY IN DYSPHORIA

by

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