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Negative Emotion Reduces Visual Working Memory Recall Variability: A Meta-analytical Review

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Abstract

Negative emotion is often hypothesized to trigger a more deliberate processing mode. This effect can manifest as increased precision of information maintained in working memory (WM) captured by reduced WM recall variability. However, some recent evidence shows that WM representations are immune to any emotional influences. Here, we meta-analyze existing evidence based on data from 13 experiments across 491 participants who performed a delay-estimation WM task under negative and neutral emotions. We find that negative emotion modestly reduces WM recall variability and increases recall failures relative to the neutral condition. These effects are moderated by participants' self-report negative experiences during emotion induction. Collectively, these data suggest that negative emotion influences how much and how well one can remember in WM.

Keyword: Negative Emotion, Working Memory, Capacity, Precision.

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Cognitive performance is often influenced by the observer's emotional states (Dolan, 2002). Clarifying the nature of these ubiquitous emotional effects on cognition is key to understanding everyday cognition (Neisser & Winograd, 1988) and improving human performance under emotional influences (e.g., eyewitness testimony; Wells, Memon, & Penrod, 2006). Substantial progress has been made in understanding the impacts of negative emotion on long-term memory. For example, information initially encoded under negative emotion (i.e., flashbulb memory; Brown & Kulik, 1977) can be remembered with greater details (Kensinger, 2007, 2009), higher fidelity (Xie & Zhang, 2017b), and elevated subjective feelings of remembering (Rimmele, Davachi, Petrov, Dougal, & Phelps, 2011; Rimmele, Davachi, & Phelps, 2012; Xie & Zhang, 2017b). In parallel with these well-documented findings on long-term memory, recent research has demonstrated similar emotional effects on information retained over a shorter period of time in working memory (WM). Specifically, negative emotion can reduce the variability in WM recall performance, potentially reflecting increased precision of the retained WM content (Spachholz, Kuhbandner, & Pekrun, 2014; Xie & Zhang, 2016; Long, Ye, Li, Tian, & Liu, 2020).

This effect is often demonstrated using the delay-estimation task (Wilken & Ma, 2005; Zhang & Luck, 2008), which provides means for experimental estimation of WM precision. In this task, participants are asked to remember some emotionally neutral stimulus features (Figure 1A), such as color, orientation, or contour shape (Figure 1B), under different emotional experiences (e.g., negative vs. neutral) induced by the presentation of affective pictures or audio

clips (Figure 1D). After a short retention interval (~ 1 s), participants try to recall one of the remembered items as precisely as possible by matching it onto a continuous circular feature space (Figure 1A). On a trial-by-trial basis, participants' WM task performance is measured as the recall error, which is calculated as the angular distance between the reported and studied feature values of the test item. This continuous measure is then subject to further mathematical modeling to produce quantitative estimates of different aspects of WM representations (e.g., Bays & Husain, 2008; Schurgin, Wixted, & Brady, 2020; van den Berg, Shin, Chou, George, & Ma, 2012; Zhang & Luck, 2008). Among the various models, the Zhang & Luck mixture model (2008) assumes that some recall errors are driven by graded WM representations captured by a bell-shaped distribution, while others, especially large errors, are driven by failed recall responses uniformly distributed in the feature space (Figure 1C; Zhang & Luck, 2008). The use of a circular feature space makes it easier to partial out the two underlying distributions to obtain an estimate of the precision of retained WM content (Xie & Zhang, 2017a; Zhang & Luck, 2008). Other models propose that large recall errors may be driven by fuzzy or weak WM traces instead of memory failures (e.g., Bays & Husain, 2008; Schurgin et al., 2020; van den Berg et al., 2012; but see Adam, Vogel, & Awh, 2017). Despite this difference in the conceptualization of the WM storage limit, the effect of negative emotion on WM precision seems to persist, regardless of whether the emotional effect on WM recall success is present or absent (Spachholz, Kuhbandner, & Pekrun, 2014; Xie & Zhang, 2016; Long, Ye, Li, Tian, & Liu, 2020).

These findings are consistent with the close interactions observed between emotion and WM. For instance, Baddeley and colleagues proposed a dedicated “hedonic detector” in the WM system (Baddeley, 2012; Baddeley, Banse, Huang, & Page, 2012). According to this hedonic

detector hypothesis, the WM system automatically assesses the emotional values of the incoming sensory stimuli, setting a reference point based on an observer's emotional experience at a given moment. This process further modulates how information is selected, represented, and retained in WM (Baddeley, 2012). Alternatively, instead of attributing emotional function to an intrinsic WM sub-process, another class of hypotheses maintains that emotional experiences can influence memory via emotional modulation of attention (Easterbrook, 1959; Huntsinger, 2013; Mather, Clewett, Sakaki, & Harley, 2016; Sharot & Phelps, 2004; Storbeck & Clore, 2005). For example, Easterbrook (1959) proposed that negative emotion narrows the focus of attention (Reisberg & Heuer, 2004; Weltman, Smith, & Egstrom, 1971) and subsequently facilitates the processing of central stimuli from the environment (Kensinger, Garoff-Eaton, & Schacter, 2007). This idea is echoed by the affect-as-information hypothesis, which holds that negative emotion often signals possible environmental dangers, thereby motivating observers to elaborate on the details of information processed under the focus of attention (Storbeck & Clore, 2005). Consistent with these ideas, previous research has shown that negative emotion can improve the qualitative aspect of cognitive processes (Chipchase & Chapman, 2013; Storbeck, 2013), potentially due to more efficient use of cognitive resources (Eysenck, Derakshan, Santos, & Calvo, 2007). These beneficial effects of negative emotion on detail-oriented processing is further dissociable from the adverse effects of negative emotion on information control (Eysenck et al., 2007). In the WM domain, induced negative emotion can sharpen the representation of information encoded into WM, leading to reduced variability in WM recall (Xie & Zhang, 2016). This precision increase may sometimes be accompanied by a reduction in one's ability to retain multiple pieces of information in WM (e.g., Figueira et al., 2017; Long et al., 2020; Mather et al., 2006; Spachtholz et al., 2014). These impacts manifest as both beneficial and detrimental effects of induced

negative emotion on WM, as revealed by the sensitive measure of continuous recall errors in the delay-estimation task (see a discussion in Xie & Zhang, 2016).

However, null results of induced negative emotion on WM have also been reported. Using similar methods, Souza and colleagues (2020) recently found that induced negative emotion failed to affect WM recall variability, except in one experiment. Despite this positive evidence, Souza and colleagues (2020) concluded that WM representations are immune to any emotional influences, especially when the induced emotional context (e.g., pictures or audio clips) is irrelevant to the content (e.g., color or orientation) of an ongoing WM task. This assertion appears to be at odds with the greater body of empirical literature regarding the influences of negative emotion on cognitive task performance that critically relies upon WM (e.g., Costanzi et al., 2019; Jackson, Linden, & Raymond, 2014; Sutherland & Mather, 2012). Furthermore, the various orthogonal experimental factors, such as the retro-cue and delay interval manipulations in Souza et al. (2020), have further complicated the interpretation of their findings. Nonetheless, as suggested by Souza and colleagues (2020), these null results seem to be in line with the expected resistance of WM to interference (Lorenc, Mallett, & Lewis-Peacock, 2021; Vogel, McCollough, & Machizawa, 2005). For WM to “work”, information retained under the focus of attention is expected to be robust to distraction from irrelevant perceptual input and any internal sources of interference (Lorenc et al., 2021); and, in principle, this includes the emotional context in which a memory event occurs (Smith, 2006; Xie & Zhang, 2018).

Given these conflicting findings and competing views, it is unclear whether and how negative emotion influences WM. This uncertainty poses a fundamental challenge to our understanding of how WM and other cognitive processes work in emotionally rich everyday life (Neisser & Winograd, 1988). The present meta-analytical review, therefore, aims to

quantitatively synthesize the relevant empirical findings (Long et al., 2020; Souza et al., 2020; Spachtholz et al., 2014; Xie & Zhang, 2016) to determine whether or not induced negative emotion reduces WM recall variability. First, we combined data from 13 experiments across 491 participants and obtained substantial evidence against the hypothesis that induced negative emotion has no impact on WM representations at all. Second, we identified a moderator often neglected but that might have substantially affected previous experimental observations (Rosenthal & Rosnow, 2008; Xie, Cappiello, Meng, Rosenthal, & Zhang, 2018). We found that the strength of self-reported negative emotion experiences across experiments could in part account for the mixed experimental findings in the previous studies.

Methods

Selection of Data for Meta-analysis

The current study used a two-stage search strategy to identify relevant studies and experiments for the meta-analysis. First, we performed a literature search in the PsycINFO and PsycARTICLE (via EBSCO), PubMed, ScienceDirect, Web of Science, and Google Scholar databases. In these searches, the following keywords and their combinations were used: “emotion,” “working memory,” “short-term memory,” “precision,” “resolution,” and “capacity.” These searches focused on papers published in English with no limit on publication date and identified 14 experiments in 4 published studies (Long et al., 2020; Souza et al., 2020; Spachtholz et al., 2014; Xie & Zhang, 2016). Second, we reviewed the protocol of these experiments, using the criteria listed in the next section. The final set included 13 experiments with a total of 491 participants (72% females, on average), as summarized in Table 1. A flow diagram for the systematic search and selection of meta-analysis samples is summarized in

Figure 2 (Moher, Liberati, Tetzlaff, Altman, & Group, 2009). We then gathered trial-level data for the selected experiments through the Open Science Framework or from the original author. Processed data and scripts for the current meta-analysis will be made available online via the Open Science Framework, <https://osf.io/ndqwy/>.

Criteria for Inclusion and Exclusion

To be eligible for the meta-analysis, an experiment should (1) use the delay-estimation WM task with a sufficient retention interval (e.g., ~1 s) between the study and test phases of the task, (2) use a circularly continuous stimulus feature (e.g., color, orientation, or contour shapes) to minimize biases in estimating random recall responses (Zhang & Luck, 2008), (3) include both negative and neutral emotion conditions, and (4) be free of additional known experimental perturbations of WM task performance (e.g., retro-cue or delay manipulation). Data from ineligible experiments or conditions may capture phenomena that are qualitatively different from the effects of interest and hence were excluded from the current meta-analysis. The rationale for the inclusion/exclusion criteria was as follows.

First, remembering visual stimuli over a very short retention interval primarily relies on sensory memory rather than WM (Cappiello & Zhang, 2016). Hence, the sensory memory condition from Spachtholz et al. (2014) and Experiment 3 from Xie et al. (2016) were excluded from the current meta-analysis. Second, data from conditions for orthogonal research questions are not included in this meta-analysis (e.g., retro-cue and prolonged delay manipulation in Souza et al., 2020). Both retro-cue (Souza & Oberauer, 2016) and prolonged delay (Zhang & Luck, 2009) can affect delay-estimate task performance. How these effects are related to the impacts of induced negative emotion on WM is an issue orthogonal to the current research focus and entails separate investigations. Third, we also excluded conditions of positive emotion on WM

representations. Positive emotion tends to show larger individual variations (e.g., Hardy & Segerstrom, 2017), making its induction more difficult in a laboratory setting based on affective images or sound clips. Certain procedures such as giving out an unexpected reward may be more efficient in eliciting positive experiences (e.g., Levine, Schmidt, Kang, & Tinti, 2012; Yang, Cook, & Isen, 2013). However, none of the reviewed experiments used these procedures.

In addition to these experiment-level criteria, we also implemented some trial-level criteria to accommodate issues related to experimental designs. For experiments using affective images, we excluded the trials when participants did not show responses to the presented emotion stimuli or when the responses rapidly terminated the presentation of the emotion stimulus (e.g., < 1.5 s or 25% of a 6 s planned exposure duration in Experiment 1 and Experiment 2a of Souza et al., 2020). Both cases would reduce the efficacy of emotion induction as acknowledged by Souza and colleagues (2020). We selected 1.5 s as a cut-off criterion for the necessary affective picture viewing time because approximately 90% of the participants had a median response time greater than 1.5 s when evaluating the emotional values of IAPS images (Xie & Zhang, 2016). Finally, to be consistent with Souza and colleagues (2020), we excluded participants with extremely low performance (average absolute recall error > 65 degrees in the 360-degree color space) in their Experiment 6, which accounted for 17% of the participants recruited for their experiment.

Coding of Experiment-level Variables

We separated the experiments by research groups, emotion induction stimuli (images or audio clips), study design (within-subject or between-subject), stimulus features for the memory task (color, shape, or orientation), and the involvement of additional manipulation (e.g., retro-cue). Among these experiments, 10 out of 13 experiments had used a set of similar IAPS images

to induce emotional experiences based on a similar within-subject design and the same rating scale. In these 10 experiments, participants viewed an IAPS image for a few seconds and then provided a rating score on a 9-point Self-Assessment Manikin (SAM) scale (1 = very negative, 9 = very positive, Bradley & Lang, 1994). These settings allow a direct comparison of the strength of self-report emotional experiences across experiments by comparing the distributions of SAM rating scores. For each participant, we evaluated the IAPS rating distributions separately for negative and neutral images. We then averaged the participants' data within each experiment to generate an experiment-level IAPS rating distribution. The central tendency of these IAPS rating distributions was assessed as the mode of the rating scores, which reflects the most common level of self-report emotional experiences at the experiment level.

Estimating the Impacts of Induced Negative Emotion on WM

We compared WM recall error distributions between the negative and neutral conditions to evaluate whether induced negative emotion would lead to less variable WM recall responses. We addressed this issue with two complementary approaches. First, to retain consistency with prior studies, we estimated WM recall variability after factoring out failed memory responses uniformly distributed across the circular feature space. Specifically, we fit recall errors by participants and emotion conditions to the Zhang and Luck (2008) mixture model based on Maximum Likelihood Estimation (MLE). As previously introduced (Figure 1C), this model assumes that the overall recall errors reflect two aspects of WM representations. For remembered WM contents, participants' recall errors tend to be small and driven by WM imprecision, manifested as the variability of a bell-shaped von Mises distribution in the circular feature space (e.g., 360 degrees for colors or 180 degrees for line orientation). The standard deviation (*SD*) of this von Mises distribution therefore serves as an inverse measure of WM precision. For non-

remembered WM contents, recall errors may mostly be driven by failed recall responses uniformly distributed across the circular feature space. The proportion of trials attributed to this uniform distribution is then inversely related to the likelihood of recall success (Pm). To minimize the variability in model fitting procedures across previous studies, we used the *MemToolbox* to harmonize the MLE procedure for the mixture model (Suchow, Brady, Fournie, & Alvarez, 2013). The resulting mixture model parameters, SD and Pm , were then compared between the negative and neutral conditions, and the effect size was measured as $r_{\text{equivalent}}$ (hereafter referred to as r , see formula below; Rosenthal & Rubin, 2003) based on t and degree of freedom (df) values of these statistical tests (also see Fritz, Morris, & Richler, 2012). These statistics and effect size estimates will be slightly different but close to those reported in the original studies.

$$r = \sqrt{\frac{t^2}{t^2 + df}}$$

Second, we evaluated the difference in the overall recall variability between the two emotion conditions without assuming the underlying theoretical model of WM recall errors. This approach focuses on identifying the variability in the data across experimental conditions that could not be accounted for by chance alone. First, we normalized recall errors by converting them to the standardized unit based on the standard deviation of raw recall errors that included both the negative and neutral conditions for each participant. This allows us to combine data across 360-degree color space and 180-degree orientation space in different experiments. A recall error of 1 in the normalized data reflects an error magnitude of 1 standard deviation of a given individual's overall recall performance, which is agnostic about any conditional difference at this stage. Second, we separated the trials into the negative and neutral conditions and took the difference of the normalized recall error distributions (negative – neutral). Third, this difference

recall error distribution was then averaged across participants and experiments to produce an overall distribution that captured the overall experimental effects.

In contrast to the first approach, the analysis of difference recall error distribution primarily focuses on the variance in overall recall errors between experimental conditions, posing minimal assumptions for the underlying generative models of WM recall performance. If negative emotion indeed reduces WM recall variability, the difference recall error distribution between emotion conditions should appear as a Mexican Hat, reflecting the difference between two bell-shaped distributions that have different widths (Müller, Mollenhauer, Rösler, & Kleinschmidt, 2005; Ryan, 1994). If, however, no emotional modulation of WM recall performance occurs, the difference of two bell-shaped distributions with similar width should produce a flat overall distribution around 0. This analysis essentially treats the data from the neutral condition as a best-predicted case for an observer's response in the negative condition. This difference recall error distribution may more reliably capture the potential difference in recall variability across experimental conditions that may not be captured by certain theoretical models (see van den Berg et al., 2012). This approach is thus complementary to the analysis of the difference in model parameters when the data from different conditions are estimated separately (Hedge, Powell, & Sumner, 2017).

We evaluated whether the difference recall error distribution follows a Mexican-Hat shape by fitting this distribution to the *Difference of Gaussians* (DOG) model (Müller et al., 2005; Ryan, 1994):

$$f_{\sigma_1, \sigma_0}(x) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{x^2}{2\sigma_1^2}} - \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{x^2}{2\sigma_0^2}}$$

where σ_1 and σ_0 represent the overall variability of recall errors under the negative and neutral conditions, respectively, and x reflects the recall error at a certain level of the difference recall error distribution, ranging from -4 to 4 with a step of 0.2 standardized unit (hence 23 data points in total). We calculated the R^2 value of the model in fitting the data and evaluated the statistical significance of this R^2 value based on an F test (Cohen, Cohen, West, & Aiken, 2013). We also calculated the bias-corrected Akaike information criterion (AIC) as another goodness-of-fit measure, based on the formula below (Burnham & Anderson, 2002):

$$AIC = N \cdot \ln\left(\frac{SS}{N}\right) + 2K + \frac{2K(K+1)}{N-K-1}$$

where N is the number of data points used for model fitting, K is the number of model parameters, and SS is the sum of the squares of the difference between the data and the fitted curve. A smaller AIC value indicates a better fit. We then generated a null model by setting $\sigma_1 = \sigma_0$ and compared it with the DOG model. We calculated the evidence ratio, $e^{-0.5\Delta AIC}$, to evaluate the likelihood that the data were better fitted by one model over the other (Burnham & Anderson, 2002).

Meta-Analysis Strategies

Combining Effect Size r . We conducted a conventional meta-analysis on r with the following steps (Rosenthal & DiMatteo, 2001). First, each r was normalized based on Fisher's Z_r transformation. Second, we tested the significance of these estimated effects separately for fixed-effect and random-effect models (Borenstein, Hedges, Higgins, & Rothstein, 2009; Rosenthal & DiMatteo, 2001). The fixed-effect model assumes the same effect size for each experiment, whereas the random-effect model assumes variable effect sizes across experiments (Borenstein et al., 2009; Rosenthal & DiMatteo, 2001). We used the mean Fisher's transformed Z_r weighted by sample size in each experiment to quantify the combined fixed-effect and evaluated the random

effect based on the DerSimonian-Laird method (DerSimonian & Laird, 1986; Hedges & Vevea, 1998). We reported two-tailed p values for these tests along with their 95% confidence intervals. We then assessed the significance of heterogeneity in the observed effect sizes across the K studies in the current meta-analysis using Cochran's Q test, which follows a χ^2 distribution with df as $K - 1$ (K is the number of effect sizes). We also reported I^2 , which reflects the percentage of variation in effect sizes due to the heterogeneity in the effect size estimates rather than chance (see Higgins & Thompson, 2002 for details).

Comparing Effect Size r . To evaluate the impact of potential moderators on the effect size estimates, we compared the effect size across the experiments based on the following formula,

$$Z = \frac{\sum(Z_r \lambda)}{\sqrt{\sum \frac{\lambda^2}{N - 3}}}$$

where λ is the contrast weight (e.g., -1 or +1, for a smaller or larger effect, summed to 0) associated with a given effect size estimate Z_r , and N is the sample size associated with Z_r . This metric allows us to examine the extent to which systematic differences merge within the current set of effect size estimates based on certain moderating variables (Rosenthal & DiMatteo, 2001).

Results

Evidence based on the Mixture Model Parameters

We first examined how induced negative emotion affected the measure of WM recall variability based on the Zhang and Luck (2008) mixture model. As previously introduced, this model factors out failed recall responses ($1 - P_m$) uniformly distributed across the circular space across trials and the variability of memory-based recall responses (SD , inversely related to precision). The two parameters of the model are thought to reflect independent aspects of the

mnemonic representations that drive WM recall performance (Adam et al., 2017; Xie & Zhang, 2017a; Zhang & Luck, 2011). In theory, it is possible that induced negative emotion can exert independent influences on *SD* and *Pm*. Alternatively, observers may retain fewer items (lower *Pm*), but with more precise WM content (hence less variable recall responses, smaller *SD*) under induced negative emotion. This trade-off can result from attention narrowing or strategic allocation of memory resources (Bays & Husain, 2008) or memory slots (Zhang & Luck, 2008) with a unified mechanism (for details, see general Discussion). Previous studies have reported that induced negative emotion can reduce WM recall variability, leading to a smaller *SD* estimate, regardless of whether this trade-off occurs or not (Long et al., 2020; Spachtholz et al., 2014; Xie & Zhang, 2016). We further examined this issue by meta-analyzing the effects of induced negative emotion on *SD* and *Pm*, separately.

First, as shown in Figure 3A, the combined effect of induced negative arousal on WM recall variability estimate (*SD*) across experiments was significantly different from the null value based on the random-effect model ($Z_r = -0.18 [-0.31, -0.05]$, $Z = -2.73$, $p = 0.006$) and the fixed-effect model ($Z_r = -0.15 [-0.24, -0.05]$, $Z = -3.10$, $p = 0.002$). For both models, the overall effect size estimates were smaller than 0 for the comparison between the negative and neutral conditions, suggesting that induced negative emotion consistently reduced WM recall variability (hence smaller *SD*). There was marginally significant heterogeneity in the observed effect sizes across experiments ($Q(12) = 20.63$, $p = 0.056$, $I^2 = 41.8\%$).

Second, the combined effect of induced negative emotion on the estimate of WM recall success rate (*Pm*) was also significant across experiments in both the random-effect model ($Z_r = -0.15 [-0.27, -0.04]$, $Z = -2.65$, $p = 0.008$) and the fixed effect model ($Z_r = -0.15 [-0.24, -0.06]$, $Z = -3.19$, $p = 0.001$). The test of heterogeneity was not significant across experiments ($Q(12) =$

16.21, $p = 0.18$, $I^2 = 25.9\%$). Overall, these meta-analysis findings suggest significant evidence for the predicted effect of reduced WM recall variability under induced negative emotion, which is accompanied by a trade-off of the number of items that an observer can effectively remember in WM (Spachholz et al., 2014).

Evidence based on the Difference Distribution of Normalized Recall Errors

Next, we investigated the impact of induced negative emotion on the overall variability in WM recall performance by looking at the difference recall error distribution between negative and neutral conditions with minimal assumptions on the theoretical model of WM. We first obtained each participant's normalized recall error distributions and then took the difference in the recall error distributions between the emotion conditions (negative – neutral). We averaged participants' data to obtain an experiment-level estimate, and then calculated the unweighted (random-effect) mean difference distribution across the experiments (Rosenthal & DiMatteo, 2001). Overall, this difference distribution at the experiment level can be well captured by the DOG model ($AIC = -308.57$, $R^2 = 0.69$, $F_{(1, 21)} = 20.98$, $p = 0.00016$, Figure 4). In contrast, the null model, in which the negative and neutral conditions were forced to have equal variance in recall errors, showed a clear misfit ($AIC = -297.42$, $R^2 < 0.01$). The difference in AIC value suggests that the DOG model is about 263 times more likely to account for the difference distribution as compared with the null model. These results suggest that induced negative emotion tends to reduce overall recall variability across experiments (also see Supplementary Figure S1 for more discussion).

A Potential Moderator: Self-report Measure of Negative Emotional Experiences

The meta-analysis results based on mixture model parameters suggest a certain level of heterogeneity in the effect of induced negative emotion on WM recall variability (Figure 3A).

Part of this heterogeneity can be attributed to known factors that have been investigated in the previous studies. For example, encoding duration and study-and-test delay duration could affect the delay-estimate task performance under induced negative emotion (Long et al., 2020; Xie & Zhang, 2016). Furthermore, a genetic factor, a deletion variant in ADRA2B, could account for some individual differences in the cognitive effects of induced negative emotion (Xie, Cappiello, et al., 2018). In the current quantitative review, we focus on additional factors that have not been previously quantified.

First, individual differences in the induced emotional experiences can be substantial and predictive of subsequent cognitive effects (Xie, W., Sing, J. L. L., Martinez-Flores, A., & Zhang, 2021). It is possible that differences in the strength of induced negative emotion experiences in different study cohorts could account for the heterogeneity in the recall variability effect. We tested this prediction by examining the data from 356 participants across 10 experiments that used the same emotional induction method (i.e., rating pre-task IAPS images in a within-subject manner) and assessment scale (i.e., the 9-point SAM valence scale). As shown in Figure 5, although these experiments reported highly consistent ratings for neutral IAPS images, a subset of experiments showed attenuated IAPS ratings for negative IAPS images than other experiments. Specifically, participants in the experiments by Souza and colleagues (2020) consistently reported a less negative value for valence rating (higher with the mode at 3) for the negative IAPS images on a 9-point scale from negative (=1) to positive (=9), whereas participants in other studies reported a more negative value for valence rating with the mode at 1 or 2. This difference is statistically significant based on a non-parametric Wilcoxon rank-sum test ($p = 0.0079$).

This raises the question of whether the difference in self-report negative emotional experiences could account for the variability in effect size estimates. We addressed this issue by

comparing the effects of induced negative emotion on WM, assessed with the mixture model, between the sets of the experiments that showed different levels of self-report emotional experiences. We found that the experiments with more negative emotion ratings (e.g., Xie et al. 2016; Long et al., 2020) showed smaller recall variability (*SD*) and recall success rate (*Pm*) in the negative emotion condition relative to neutral conditions. In contrast, this effect was much more attenuated in the experiments with lower levels of negative emotion ratings (e.g., Souza et al., 2020). A contrast analysis comparing effect size estimates from these two sets of experiments has supported this observation (*SD* effect size in *Zr*: -0.27 vs 0.0004, $Z = 2.26$, $p = 0.024$; *Pm* effect size in *Zr*: -0.26 vs -0.02, $Z = 2.39$, $p = 0.017$). This result is not likely to be driven by a large variability in the affective images used across the experiments, as Xie et al. (2016) and Souza et al. (2020) used an identical set of affective images. This finding could instead result from the individual differences in the responses to affective images or from procedural differences in emotional induction. Taking in account these differences is important to interpret the mixed findings in the literature (Rosenthal & Rosnow, 2008).

Second, we have examined some additional potential moderators, such as whether the emotion induction procedure was implemented in a trial-by-trial random design or blocked design, the gender ratio of the sample within an experiment (as subject-by-subject gender information is not available in some experiments, see similar treatment in Mor & Winquist, 2002; Xie et al., 2018), and the tested stimulus feature (color vs. non-color). We found no statistically significant difference for effect sizes estimates in these comparisons ($ps > .10$).

Discussion

The current study has reviewed and meta-analyzed WM recall performance in 13 experiments across 491 participants based on the delay-estimation paradigm. We have obtained significant evidence that induced negative emotional context can reduce moment-by-moment WM recall variability for emotionally neutral memory information, potentially due to increased WM precision as a result of boosted focal attention under negative arousal (Huntsinger, 2013; Mather et al., 2016; Sharot & Phelps, 2004). This precision effect is captured by both model-based WM precision estimate and the analysis of the difference in recall error distributions between negative and neutral conditions without assuming the generative model for recall performance in the delay-estimation task. We have also found that the impact of induced negative emotional on WM recall behavior is moderated by the strength of self-reported negative emotional experiences. Specifically, experiments that have elicited more negative experiences from the emotion stimuli tend to show less variable WM recall performance and less retained WM items. Together, these findings suggest that WM encoding and storage for emotionally neutral information is under the influence of emotional context, in contrast to the idea that WM should be immune to any emotional influence (Souza et al., 2020).

Overall, these findings are in line with the previous research on how negative emotion modulates detail-oriented or qualitative aspects of cognitive processes (Chipchase & Chapman, 2013; Eysenck et al., 2007; Storbeck, 2013; Storbeck & Clore, 2005), including granularity of memory representations (e.g., Kensinger, 2009) and quantitative aspects of memory, such as WM capacity (e.g., Figueira et al., 2017). However, the emotional memory literature has largely assessed memory for emotional content (Bennion, Ford, Murray, & Kensinger, 2013). Extending these findings to memory for neutral information under an emotional context may address an

important gap in the emotional memory literature (e.g., flashbulb memory). That is, the difference in memory performance for emotionally charged information (e.g., a snake) and neutral information (e.g., a chair) is often subject to alternative interpretations because various sources of confounds (e.g., sensory differences) other than the emotional values of stimuli could lead to the observed differences in memory performance (Kensinger & Schacter, 2008). In line with this concern, neuroimaging and deep neural network modeling have identified reliable sensory differences in affective images (Kragel, Reddan, LaBar, & Wager, 2019), which could further modulate image memorability (Rust & Mehrpour, 2020). To distinguish the emotional impacts on memory processes from the intrinsic memorability of affective stimuli, it is thus critical to articulate how induced emotional experiences influence the memory of neutral information (Xie & Zhang, 2017b).

In addition to these empirical contributions, the current meta-analytical review provides several novel theoretical contributions. First, this study provides an integrated account of both detrimental and beneficial effects of induced negative emotion on ongoing mental processes, such as WM. These effects are closely tied to multifaceted impacts of emotion on attentional processes (Eysenck et al., 2007), considering the close relationship between attention and WM (Cowan, 2001). On the one hand, induced negative emotional experiences tend to interrupt ongoing mental processes and tax control-related WM processes (e.g., see a review in Schweizer et al., 2019 for a moderate but significant overall effect size). Consequently, tasks that capture control-related WM functions (e.g., the n-back task) often show reduced performance under negative emotion (e.g., Choi et al., 2013; Schoofs, Preuß, & Wolf, 2008; Shackman et al., 2006). On the other hand, negative emotion could also increase the efficiency of information processing (Eysenck et al., 2007; Xie, W., Sing, J. L. L., Martinez-Flores, A., & Zhang, 2021). As a result,

memory items retained under the focus of attention in WM may be encoded with greater precision. Alternatively, this trade-off between the total amount of information retained in WM and the quality of remembered content could also be a result of a change in task strategy or information processing style induced by negative emotion (Chipchase & Chapman, 2013; Storbeck, 2013; Storbeck & Clore, 2005). Specifically, negative emotion, similar to certain experimental manipulations such as attentional cuing (Zhang & Luck, 2008), can lead to strategic trading off capacity for precision, even though the opposite direction of trading off precision for capacity seems implausible (Zhang & Luck, 2008, 2011). These moment-by-moment effects of emotion may lead to longer-term effects of emotion on cognition (e.g., boosted long-term memory precision under induced negative emotion, Xie & Zhang, 2017c). Future research needs to investigate how emotion modulates the transfer of information across different storage states in the memory system (Tyng, Amin, Saad, & Malik, 2017), especially the neurobiological underpinning of these processes.

Second, the current study has revealed a potential moderator of the experimental effect of induced negative emotion on WM. Although the induction and assessment of emotional experiences have been extensively investigated in the past several decades (e.g., Bradley & Lang, 1994; Miers, Blöte, Sumter, Kallen, & Westenberg, 2011; Schubert, 2011; Siedlecka & Denson, 2019; Vuoskoski & Eerola, 2011), emotional experiences induced using laboratory stimuli and procedures can vary significantly due to individual differences in various factors such as emotion modulation and resilience (Chen et al., 2018; Quigley, Lindquist, & Barrett, 2014; Xie, W., Sing, J. L. L., Martinez-Flores, A., & Zhang, 2021; Xie, Cappiello, et al., 2018). Besides implementing more effective emotion induction procedures (Quigley et al., 2014), another essential step is to assess how the strength or intensity of induced emotional experiences across participants could

modulate our experimental observations. This treatment of self-report emotional experience as a continuous instead of a binary variable (e.g., negative versus neutral) is consistent with the contemporary understanding of emotion as a theoretical construct (Mauss & Robinson, 2009). Nevertheless, considering that emotional experiences are multifaceted, future research should include multimodal assessments of induced emotional experiences, such as more objective measures of emotional experiences (e.g., pupil sizes, Xie, W., Sing, J. L. L., Martinez-Flores, A., & Zhang, 2021), to provide a better evaluation of the effects of induced emotion on cognition.

There are several cautious notes regarding the current meta-analytical findings. First, despite some previous efforts in examining how positive emotion may affect WM (e.g., Ashby, Valentin, & Turken, 2002; Costanzi et al., 2019; Yang et al., 2013), laboratory induction of positive emotion appears anodically more challenging than the induction of negative emotion, especially for a long experimental session. Certain procedures, such as giving the participant an unexpected reward (e.g., Levine, Schmidt, Kang, & Tinti, 2012; Yang, Cook, & Isen, 2013), may be more effective in inducing positive emotional experiences. However, these procedures have not been implemented in the previous studies reviewed here. As it is unwarranted to expect opposite effects of negative and positive emotion on an ongoing cognitive task (see more discussions in Xie & Zhang, 2016), future research should use more effective positive emotion induction procedures to elucidate the relationship between positive emotion and WM recall behavior. Second, the studies discussed in the current meta-analysis have focused on the difference between negative versus neutral emotion, which may be an oversimplification of the complex affective experiences and the interactions between emotion and memory (Levine & Pizarro, 2004). Some recent studies have investigated how different affective dimensions (e.g., arousal and motivation) may influence WM storage or control-related processes (Costanzi et al.,

2019; Krawczyk & D'Esposito, 2011; Xie, Li, Zou, Sun, & Shi, 2018; Yüvrük, Kapucu, & Amado, 2020). It is therefore of great interest to further articulate how these affective or conative factors influence WM recall behavior.

Conclusion

This study provides meta-analytical evidence for the beneficial effect of induced negative emotion on WM recall variability, despite the detrimental effect of induced negative emotion on the likelihood of maintaining a given WM item. These effects are further modulated by the strength of self-reported negative emotional experiences. The current review thus promotes our understanding of the complex relationship between emotion and cognition.

Author Note

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Figure Legends

Figure 1. Paradigms and a model used in prior research to examine how induced negative emotion affects visual working memory (WM) recall behavior. (A) In a typical within-subject design study, emotional experience is induced by exposing the participant to an affective image and having them provide an affective rating of the image on a Self-Assessment Manikin scale (Bradley & Lang, 1994), before completing a delay-estimation task. (B) A variety of stimulus features in a circular space have been used in the delay-estimation task to examine visual WM recall behavior, including colors, orientations, and contour shapes. (C) Participants' performance in the delay-estimation task (i.e., recall errors, black line) is often modeled as a mixture of noisy retained WM contents captured by a bell-shaped distribution (red line) and failed recall responses uniformly distributed in a feature space (green line). (D) In a typical between-subject study, participants' WM task performance is often compared before* and after they immerse themselves in an emotional event (e.g., recalling sad memories while listening to sad music played in the background) to elicit emotional experiences. Note: *pre-induction test is not always included. The photo used in this figure is from <https://www.flickr.com> licensed under the Creative Commons license.

Figure 2. Flow diagram for the systematic literature search and selection of meta-analysis samples. n represents the number of experiments.

Figure 3. Effect size estimates for the impacts of induced negative emotion on mixture model parameters. SD captures the variability of retained WM content and is hence reflective of WM precision. Pm captures the likelihood of recall success. Each dot represents an effect size estimate in an experiment, with the dot size reflecting the weights in a fixed-effect model. The error bars represent 95% confidence intervals.

Figure 4. Overall difference in recall error distributions between negative and neutral conditions across experiments. Each dot represents an unweighted (random-effect) effect size estimate at certain location of the normalized recall error distribution. The error bars represent standard errors of these mean estimates. The red line represents the fit of the Difference of Gaussians (DOG) model. The light green line represents the null effect model, in which negative and neutral conditions are assumed to have equal overall variance in the recall error distribution.

Figure 5. Distributions of participants' subjective ratings of the IAPS images across studies. (A) Data from Xie et al. (2016) and Long et al. (2020). (B) Data from Souza et al. (2020). Each thin line represents data from one experiment. The thick lines represent the average value (unweighted). Error bars represent standard errors of mean estimates.

Figure 1. Paradigms and a model used in prior research to examine how induced negative emotion affects visual working memory (WM) recall behavior. (A) In a typical within-subject design study, emotional experience is induced by exposing the participant to an affective image and having them provide an affective rating of the image on a Self-Assessment Manikin scale (Bradley & Lang, 1994), before completing a delay-estimation task. (B) A variety of stimulus features in a circular space have been used in the delay-estimation task to examine visual WM recall behavior, including colors, orientations, and contour shapes. (C) Participants' performance in the delay-estimation task (i.e., recall errors, black line) is often modeled as a mixture of noisy retained WM contents captured by a bell-shaped distribution (red line) and failed recall responses uniformly distributed in a feature space (green line). (D) In a typical between-subject study, participants' WM task performance is often compared before* and after they immerse themselves in an emotional event (e.g., recalling sad memories while listening to sad music played in the background) to elicit emotional experiences. Note: *pre-induction test is not always included. The photo used in this figure is from <https://www.flickr.com> licensed under the Creative Commons license.

Figure 2. Flow diagram for the systematic literature search and selection of meta-analysis samples. *n* represents the number of experiments.

Figure 3. Effect size estimates for the impacts of induced negative emotion on mixture model parameters. *SD* captures the variability of retained WM content and is hence reflective of WM precision. *Pm* captures the likelihood of recall success. Each dot represents an effect size estimate in an experiment, with the dot size reflecting the weights in a fixed-effect model. The error bars represent 95% confidence intervals.

Figure 4. Overall difference in recall error distributions between negative and neutral conditions across experiments. Each dot represents an unweighted (random-effect) effect size estimate at certain location of the normalized recall error distribution. The error bars represent standard errors of these mean estimates. The red line represents the fit of the Difference of Gaussians (DOG) model. The light green line represents the null effect model, in which negative and neutral conditions are assumed to have equal overall variance in the recall error distribution.

Figure 5. Distributions of participants' subjective ratings of the IAPS images across studies. **(A)** Data from Xie et al. (2016) and Long et al. (2020). **(B)** Data from Souza et al. (2020). Each thin line represents data from one experiment. The thick lines represent the average value (unweighted). Error bars represent standard errors of mean estimates.

Table 1. Experiments included in the meta-analysis of the effects of induced negative emotion on visual WM recall behavior.

ID	Exp.	Country	N ^a	%F	Design	Emotion Induction	Task Feature	Note
1	SP1	DE	78	0.81	Between	Audio + autographic retrieval	Color	Sensory memory condition is not included
2	XZ1	USA	18	0.72	Within, blocked	Visual, IAPS	Color	Sensory memory experiment is not included
3	XZ2	USA	19	0.63	Within, mixed	Visual, IAPS	Shape	
4	LO1	CN	30	0.63	Within, blocked	Visual, IAPS	Orientation	
5	LO2	CN	30	0.63	Within, blocked	Visual, IAPS	Orientation	Effect size estimates from 200 ms and 500 ms presentation conditions are averaged for an experiment-level effect size.
6	LO3	CN	30	0.63	Within, blocked	Visual, IAPS	Orientation	
7	AS1	SW	22	0.73	Within, mixed	Visual, IAPS	Color	
8	AS2a	SW	20	0.80	Within, mixed	Visual, IAPS	Color	Retro-cue condition not included
9	AS2b	SW	20	0.85	Within, mixed	Visual, IAPS	Color	
10	AS3	SW	42	0.83	Within, mixed	Visual, IAPS	Orientation	
11	AS4	DE	17	0.88	Within, mixed	Visual, IAPS	Color	Long decay condition is not included
12	AS5	PT	40	0.62	Between	Visual, IAPS+Audio	Color	Retro-cue condition is not included
13	AS6	USA, online	125	0.57	Within, mixed	Visual, IAPS	Color	

Note: Exp. = Experiment; XZ1-2 = Exp. 1-2 of Xie and Zhang (2016); SP = Spachtholz et al. (2014); LO1-3 = Exp. 1-3 of Long et al. (2020); AS1-6 = Exp. 1-6 of Souza et al. (2020); DE = Germany; SW = Switzerland; CN = China; PT = Portugal; USA = United States; IAPS = International Affective Picture System; %F = % of females. a. The sample size here represents effective sample size after applying the exclusion criteria by the original authors.