

# Reducing Traumatic Memory Intrusions by Timing Their Re-Encoding: An Application of Computational Modeling to Mental Health

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## Abstract

Intrusive memories are disruptive to daily functioning and detrimental to well-being; unfortunately, the presence of these memories is a defining characteristic of post-traumatic stress disorder (PTSD). Although increasingly understood as a memory disorder, current trauma management and recovery strategies for PTSD do not often take principal memory theories into account. Many common practices, such as delayed processing after trauma exposure and spaced therapy sessions, might inadvertently strengthen the retention of intrusive memories in the long-term. In this paper, model simulations show that altering the timing of different presentations of emotional stimuli might affect subsequent intrusions. Experimentally, we demonstrated through a two-day within-subject image presentation task that when emotional images are presented in spaced intervals (as opposed to consecutive, “massed” presentation), the perceived frequency of intrusions for the mass-presented emotional images during the 24 hours after first exposure were significantly lower than spaced images. Our study presents a novel strategy that can potentially mitigate the frequency of intrusive post-traumatic memories, highlighting the advantages of translational applications of computational cognitive models to mental health.

**Keywords:** PTSD; memory; intrusive memories; trauma management; trace theory; spacing effect.

## Introduction

Posttraumatic stress disorder (PTSD) is a stressor-related psychiatric disorder that affects around 4% of the population (Liu et al., 2017). Among occupations that involve repeated exposure to potentially traumatizing events such as firefighters and military service members, this prevalence can be as high as 37-57% (Obuobi-Donkor, 2022). A defining characteristic of PTSD is the presence of *intrusive memories* (Marks et al., 2018), which are detrimental to daily functioning and well-being. An effective trauma

management strategy should be able to predict and control the frequency of these intrusions to minimize their negative impacts on mental health.

Although PTSD is increasingly understood as a *memory* disorder, principles of memory research have not played a prominent role in trauma management. For example, the spacing effect (e.g., Cepeda et al., 2008) posits that events are remembered better when they are repeated at longer, rather than shorter, intervals. This suggests that the timing of the reactivation of memory traces is crucial in how resistant they are to forgetting. For memories that are distressing, the frequency of reactivation is also crucial to how they may become prone to unwanted intrusions.

A common course of action for post-traumatic therapies is weekly therapy sessions, during which individuals undergo guided retrievals. As the patient improves, therapy sessions may be spaced further apart, with “booster” sessions scheduled if needed. Aforementioned memory principles suggest that this may actually be further reinforcing trauma memories; massed, or more frequent therapy sessions with guided reactivations of these memories may be a more effective method. This is somewhat similar to exposure therapy in PTSD, where guided confrontations of the traumatic memory serve to desensitize and control strong emotional reactions; the objective is to discourage avoidance, which would make the fear worse and builds further sensitization (Rothbaum et al, 2002).

The practice of extended rest periods between re-exposures is not uncommon: first responders are often encouraged to take an extended period of rest after experiencing a potentially distressing or traumatic event before returning to the field. Content moderators who must view hours of disturbing content, are also encouraged to take breaks in-between. According to the spacing effect, this interval between re-exposures may inadvertently counteract the goal

of recovery after trauma exposure, promoting further retention of intrusive memories in the long term. Although the practice of rest periods and spaced sessions may seem beneficial, they - from a memory theory standpoint - exactly replicate the type of conditions that *maximize* retention, thus further consolidating the traumatic memories.

This study proposes that an approach contrary to traditional methods may be more effective in reducing the activation of traumatic memories. This approach is characterized by *massed* presentations, that is, by experiencing reactivations of a memory at short, rather than long, intervals. The current study adopts a simple image-based visual stimuli design, simulating the core processes involved in the formation of intrusive memories – encoding and retrieval – and by testing recall.

The goal of this experiment is to test whether massed or spaced presentations will yield differences in later intrusion frequencies. We predict that with this task design, the differences in presentation sequence (massed or spaced) will be sufficient to evoke differences in the frequency of intrusion for emotionally charged “negative” images. Specifically, we hypothesize that while the perceived distress of the intrusions will be similar for massed and spaced negative images, images that are mass presented will have a lower intrusion frequency than space presented images during the 24 hours after the first exposure.

## Materials and Methods

### Participants

Twenty-seven psychology undergraduates (aged 18 to 22; 19 female) were recruited from University of Washington and participated in our study exchange for extra credits in academic courses. To avoid unintended psychological side effects due to exposure to the emotionally charged images, participants were screened beforehand for depression, PTSD, and specific phobia with the Personal Health Questionnaire Version 9 (PHQ-9), Post-Traumatic Diagnostic Scale (PTSD-PDS) questionnaire, and the Severity Measure for Specific Phobia for Adults, and were excluded if they exhibited any signs of PTSD (scored  $\geq 4$  for PTSD-PDS) or scored  $\geq 10$  in the PHQ-9, or had any specific phobias at all (Kroenke et al., 2002; Foa et al., 1997; American Psychiatric Association, 2013). One participant was excluded for having a below-chance performance in the image recognition task. All of the procedures were approved by the Institutional Review Board at the University of Washington.

### Experimental Design

The experiment had a two-day longitudinal, 2-by-2, within-subject design, with the two factors being the mode of *presentation* (spaced vs. massed) and the stimulus *valence* (neutral vs. negative images). Each participant was tested on two consecutive days. On the first day, they were asked to rate individual images based on how distressing they were. The images varied in emotional valence and presentation mode. On the second day, participants performed an image

recognition task and indicated whether they recognized the image, whether they had experienced memory intrusions associated with each image in the past 24 hours, and how distressing the intrusions were.

### Visual Stimuli

Intrusive memories are often vivid and mental imagery-based (Pearson et al., 2015), so we settled on using visual stimuli for our study. Specifically, the experimental stimuli consisted of 16 negative images and 16 neutral images from the Nencki Affective Picture System (NAPS) database (Marchewka et al., 2014). Images were selected according to prefixed criteria for valence and arousal, and were also validated in a pilot study. A roughly equal number of images were selected from each of the five possible categories (“Faces”, “People”, “Animals”, “Landscapes”, and “Objects”).

To simulate the re-experiencing of a traumatic event, four variations of each of the 16 negative and 16 neutral images were presented, with different intervals between subsequent presentations. They were automatically generated by applying 2D transformations (cropping, shearing, and distortions) to the original; these transformations made the images slightly different from each other, but still recognizable as depicting the same object or event. These variations were used to simulate the creation and repeated exposures to the same memory, similar to content moderators needing to review many images of the same scene. Presenting variations instead of the same image repeatedly simulates more of a natural memory retrieval process where components or specific cues are being recalled, rather than the exact, detailed visual imagery. This can also ensure the attentiveness of the participants so that they are encoding every presentation.

Images were either mass presented (variations of the same image are presented one after the other) or spaced (variations of the same image are presented at longer intervals). This simulates memories that are created and reactivated with shorter intervals in-between (massed), or longer intervals in-between (spaced).

In addition to the experimental stimuli, another set of 32 neutral images were selected as filler stimuli. Four of these images were placed at the beginning and four at the end of each of the four experimental blocks (see Figure 1) to ensure that, despite order randomization, there was a minimum distance of eight stimuli between two subsequent presentations of images in the spaced condition. Filler images were not critical to our predictions and will not be discussed in the Results section. On Day 1, a total of 64 images, including negative, neutral and filler images, were rated by participants.

For the image recognition task 24 hours later, a third set of 32 images (16 neutral, 16 negative) were selected from the NAPS database to be used as foils in the recognition task. Each foil was chosen to match the corresponding experimental stimulus in both content (e.g., both of them depict scenes of a car accident) and valence. The same three

questions (recognition, intrusion, distress) were asked for all the images, including foil images.

## Procedures

The experiment consisted of two supervised experimental sessions taking place 24 hours apart. For the first session, participants completed an Image Rating Task, where they were asked to rate how distressing they found each image by pressing one of the number keys on the top row of a standard keyboard, ranging from 1 (“not distressing at all”) to 9 (“extremely distressing”). The act of rating was to ensure that participants spent time encoding the stimulus (rather than looking away) and to obtain subjective measures of their perceived emotional impact.

Neutral and negative images were evenly divided and randomly assigned to one of two conditions for every participant. In the mass-presentation condition, four variations of the same image were presented consecutively. In the spaced-presentation condition, four variations of the same image were separated by blocks; the entire set of presentations was divided into four blocks (with short breaks in between). The exact order of presentation of each trial was randomized for each participant, with the constraint that massed presentations of the same image were always consecutive within a block, and spaced presentations of the same image occurred once in every block. Figure 1 provides a visual illustration of this design. As a result, spaced images were separated, on average, by 35 intervening trials or about 8 minutes, and massed images by zero intervening trials and < 1 minute.

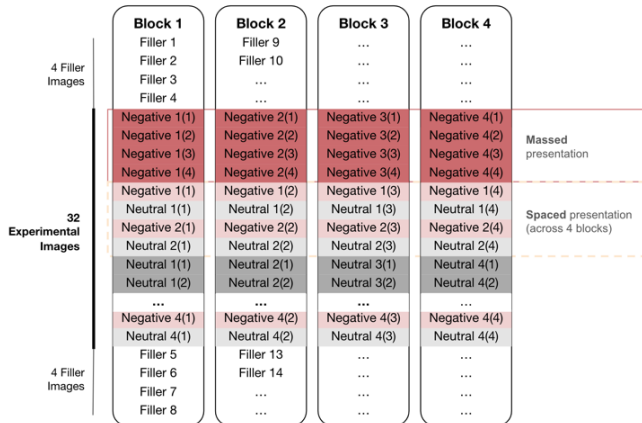


Figure 1: How different image presentations were spread across the four experimental blocks.

The second session took place 24 hours later. During this session, participants completed an image recognition task. They were presented with all of the 32 experimental images and the 32 content- and valence-matched foils in random order. For each of the 64 trials, one image (or foil) was displayed, and participants were asked: (1) Whether they the image had been seen the day before (Yes/No); (2) The perceived frequency of intrusions associated with that image during the past 24 hours (“how often thoughts of this image popped into your mind”) on a scale from 1 (no intrusions) to

9 (extremely frequent intrusions); and (3) the perceived level of distress associated with the intrusions (1 for no distress, 9 for extremely distressing). As in Day 1, all answers were entered by pressing a numeric key on the number row of a standard keyboard.

## Statistical Models for Data Analysis

All dependent variables from the experiment were analyzed with a hierarchical linear model of the form:

$$Y_{p,i} = \beta_0 + \beta_1 M_i + \beta_2 V_i + \beta_3 P_i V_i + \gamma_{0,i} + \gamma_{1,p} + \gamma_{2,p} V_{p,i} + \varepsilon_{p,i}$$

where  $Y_{i,p}$  is the response (RT, accuracy, or perceived frequency of intrusion) given by the  $p$ -th participant to the  $i$ -th image;  $M_i$  is the presentation *mode* (massed or spaced) of the  $i$ -th image;  $V_i$  is its *valence* (negative or neutral);  $\gamma_{0,i}$  is an image-specific intercept, and  $\gamma_{1,p}$  and  $\gamma_{2,p}$  are participant-specific intercepts and slopes across image valences. Note that the model includes a participant-specific slope to account for individual differences in the perceived *valence* of images, but no individual slope for participant differences in presentation mode; this is because we assume the presentation effect to be constant across individuals. Across all analysis, this statistical model was found to provide a significantly superior fit to the data when compared, through an ANOVA, to simpler models with fewer or no random effects ( $p < 0.01$  in all comparisons). The model was also consistently superior to a model that replaced the valence-specific slope with a presentation-specific slope. All statistical models were fitted using the lme4 package in R (Bates et al., 2015).

## Theory and Predictions

Our predictions are based on an established model of long-term declarative memory that also captures the spacing effect. Note that, although multiple accounts of the spacing effect have been proposed, Walsh et al (2018) demonstrated that they all fit the empirical data similarly well; thus, our predictions are not tied to the specific model we chose.

In this case, we selected the model proposed by Pavlik and Anderson (2005; 2008), which can be seen as an implementation of the multiple trace theory (Stocco et al., 2024). It assumes that memories are created by the accumulation of individual episodic traces encoded every time the same information is encountered. Each trace independently decays over time according to a power law (Newell and Rosenbloom 1981). The odds of retrieving a memory  $m$  at time  $t$  are proportional to its activation  $A(m, t)$ , a scalar quantity that approximates the log odds of retrieving any of its component traces, as shown in Eq. (1).

$$A(m, t) = \log \sum_i [t - t(i)]^{-d(i)} \quad (1)$$

In Eq. 1,  $t(i)$  is the creation time of the  $i$ -th trace and  $d(i)$  is its characteristic decay rate. Each trace-specific decay rate depends on the residual activation of the memory at the time the trace was created (Pavlik and Anderson 2005; Sense et al.

2016), plus a fixed component  $\phi$  that is characteristic of an individual

$$d(i) = e^{A(m, t = t(i))} + \phi \quad (2)$$

Here, Eq. (2) demonstrates that the higher the memory’s activation, the higher the decay rate. This explains the spacing effect: traces closer in time have higher decay rates because of the memory’s greater activation  $A(m, t)$  at time  $t(i)$ , making these mass-presented traces poorly retained on the long-term.

### Predicted Effects of Presentation

To predict the effects of spacing, we need to have an approximate idea of the value of  $\phi$ . Thankfully, a number of studies (Zhou et al., 2021; Van Rijn et al, 2009; Sense et al., 2016; Capik et al., 2024) have provided a reliable estimate for the value of  $\phi$  in college undergraduates, with the estimate being  $\phi = 0.30$ . As described above, in our paradigm mass-presented images had an average spacing of  $< 1$  min, while spaced-presented images were separated by  $\sim 8$  minutes. Based on these parameters, it is possible to simulate the predicted time course of activation of a memory in the two conditions over a period of 24 hours. Figure 1 presents the results of these simulations.

As expected, the model predicts that spaced images would retain greater activation even after 24 hours. Because a memory’s activation represents the log-odds of its retrieval, a difference in log odds represents the log of the odds ratio. After 24 hours, the difference in activation between massed and spaced images is 0.31 (Figure 2), which implies that an image in the spaced condition is approximately  $e^{0.31} = 1.36$  times more likely to have been retrieved in the previous 24 hours.

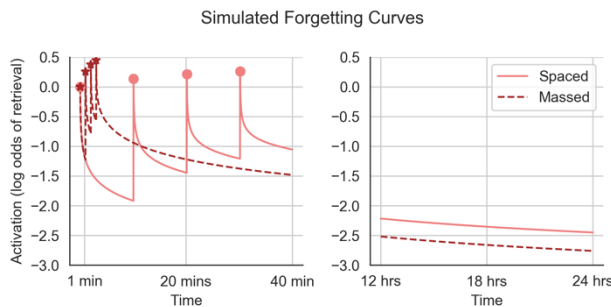


Figure 2: Simulated forgetting curves for massed and spaced-presented images. Points mark different encodings. It should be noted that each peak depicts a memory trace that was created after the initial event; trend still applies regardless of valence.

### Predicted Effects of Valence

The model described above has also been expanded to simulate emotional memories (Larue et al., 2018) and traumatic memories in PTSD (Smith et al., 2021). In both of these accounts, the emotional impact of a memory results in a constant term,  $I(m)$ , that is added to its activation and is proportional to the (negative) valence of the stimulus. In the

model, this translates to a vertical shift of the two curves in Figure 2. In the model by Smith et al (2021), this additional term accounts for the intrusive nature of traumatic memories, since their intrinsically higher activation makes them more likely to intrude during a guided memory retrieval—which would further increase their activation, potentially resulting in a positive feedback loop.

Both Larue et al. (2018) and Smith et al. (2021)’s accounts posit that the emotional valence of a memory is not affected by its activation, but to the valence of its component traces. Because the distress evoked by an intrusion should be proportional to its valence, and, in our study, each trace represents an encoding of the same image, we predict that the perceived distress associated with a memory would *not* be affected by its presentation mode.

## Results

### Perceived Distress of Negative and Neutral Images

As a first step, we examined the valence ratings of images used in our experiment. This comparison was to verify that our experimental stimuli had the necessary intensity to create memory intrusions, and that the presentation mode would not affect the way images are perceived at encoding. This was confirmed by a statistical analysis carried out with the hierarchical linear model described above (see “Data Analysis” section), which uncovered a significant main effect of image valence ( $\beta = -3.4, p < 0.001$ ) but no effect of presentation mode ( $\beta = -0.17, p = 0.365$ ) nor an interaction ( $\beta = 0.11, p = 0.662$ ). As expected, negative images were given higher distress ratings ( $M = 5.36, SD = 0.99$ ) than neutral ones ( $M = 1.56, SD = 0.43$ ; See Figure 3).

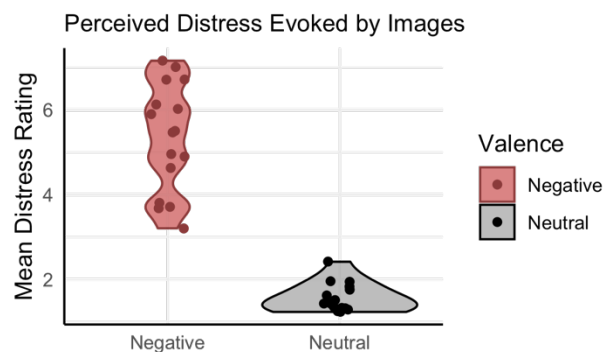


Figure 3. Density distress ratings of images. Points represent mean valence ratings for each image across all participants.

### Recognition Accuracy

Next, we verified that participants had formed and retained accessible memories of the stimuli by analyzing the accuracy of their choices in the forced-choice recognition test on Day 2, 24 hours after their first exposure to the stimuli. Figure 4 below depicts the mean recognition accuracies in each experimental condition.

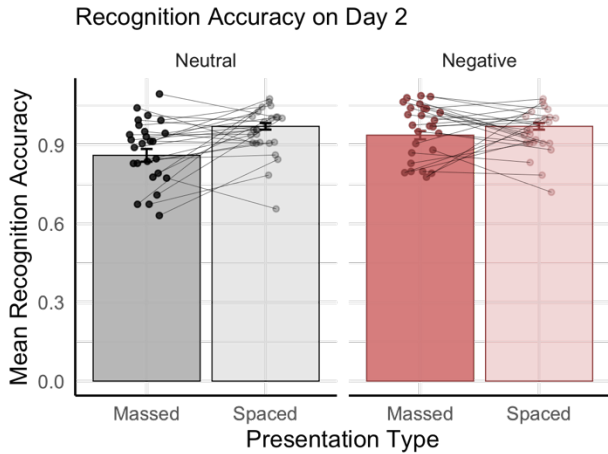


Figure 4: Mean recognition accuracy. Bars represent means; points and lines represent individual participants.

On average, participants were highly accurate, recognizing  $94\% \pm 6\%$  of the stimuli. A statistical analysis, conducted with a logistic version of the hierarchical linear model described above, showed no significant effect of either presentation mode (Odds Ratio = 2.51,  $p = 0.081$ ) or image valence (OR = 0.39,  $p = 0.10$ ) and no significant interaction between the two factors (OR = 2.47,  $p = 0.208$ ). Thus, possible differences in the number of memory intrusions evoked by different conditions cannot be ascribed to differences in how stimuli are recalled.

### Effects on Perceived Distress of Memory Intrusions

As noted above, one of the predictions of the model is that presentation mode should not affect the distress evoked from intrusive retrievals. As expected, our results show that the perceived distress of intrusions of massed images did not differ significantly from perceived distress of intrusions from spaced negative images (Figure 5). Correspondingly, the hierarchical linear model uncovered a main effect of image valence ( $\beta = -3.05$ ,  $p < 0.001$ ), with intrusions from negative images, unsurprisingly, being perceived as more distressing ( $M = 4.34$ ,  $SD = 2.04$ ) than those of neutral images ( $M = 1.27$ ,  $SD = 0.52$ ). The same model, however, uncovered no main effect of the presentation mode ( $\beta = 0.01$ ,  $p = 0.92$ ) and no interaction between presentation and valence ( $\beta = 0.06$ ,  $p = 0.70$ ).

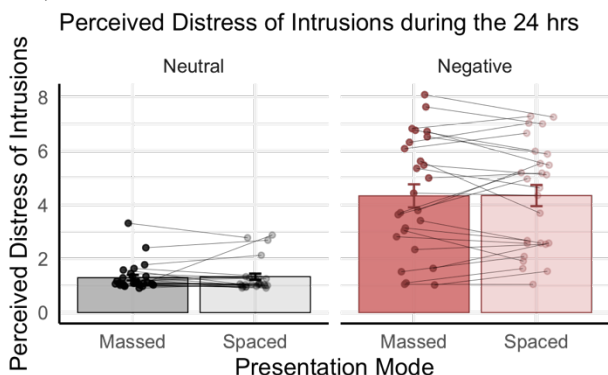


Figure 5: Perceived distress of intrusions. Bars represent means; points and lines represent individual participants.

### Effect of Spacing on Frequency of Intrusion

Lastly, we tested the most important prediction derived from our simulations: whether the frequency of intrusions for the spaced-presented images was higher than for massed-presented images. The results are depicted in Figure 6. A statistical analysis conducted with the usual hierarchical linear model showed that both image valence ( $\beta = -0.76$ ,  $p = 0.006$ ) and presentation mode ( $\beta = 0.64$ ,  $p < 0.001$ ) had a significant effect on the perceived frequency of intrusion. Unsurprisingly, intrusions were judged as occurring more frequently for negative images ( $M = 2.55$ ,  $SD = 1.63$ ) than for neutral ones ( $M = 1.52$ ,  $SD = 0.84$ ). Consistent with our hypotheses, intrusions were also judged to occur more frequently for spaced-presented images ( $M = 2.22$ ,  $SD = 1.56$ ) than for massed-presented ones ( $M = 1.86$ ,  $SD = 1.17$ ).

We also uncovered a significant interaction between valence and presentation mode ( $\beta = -0.55$ ,  $p < 0.001$ ), with the difference between massed- and spaced-presented stimuli being amplified for negative images (Figure 5). The presence of such interaction is also consistent with our model, which predicts that both image valence and presentation mode have an additive effect on a memory's activation; since activation reflects the *log* odds of retrieval, this translates to a *multiplicative* effect on the retrieval probabilities. Memory intrusions ultimately depend on the memory's baseline activation (Smith et al., 2021), and the interaction simply reflects the product of the individual effects of valence and presentation.

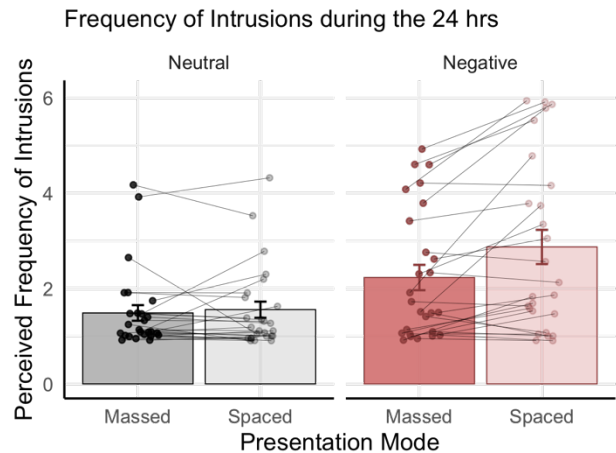


Figure 6: Perceived frequency of intrusions. Bars represent means; points and lines represent individual participants.

### Model Predictions vs. Observed Data

So far, our data has been analyzed to verify *qualitative* predictions derived from our model—for example, the prediction that massed-presented negative images would lead to fewer memory intrusions than spaced-presented ones. However, as shown in Figure 2, our computational model makes precise *quantitative* predictions. Specifically, the

model predicts that the perceived frequency of intrusions for spaced-presented images for an individual would be approximately  $e^{0.31} = 1.36$  larger than the number of intrusions that individuals reported for massed-presented ones. This difference is driven by the spacing effect; furthermore, since the spacing of stimuli was approximately the same for all participants, it should be possible to predict each participant's observed intrusion frequency for spaced-presented images by multiplying the frequency of intrusion of massed-presented images by 1.36. A possible source of individual variability is the perceived valence of emotional images, which is highly subjective and affects the number of intrusions. The additional effect of valence ( $V$ ), however, can be estimated by comparing the difference in intrusion frequency ( $F$ ) between negative and neutral massed-presented images:  $V = F_{mass,neg} - F_{mass,neu}$ . Thus, the predicted frequency of spaced neutral images is  $1.36 \times F_{mass,neu}$ , and the frequency of intrusions for spaced negative images is  $1.36 \times (F_{mass,neu} + V)$ . Figure 7 plots the observed frequency of intrusions for spaced-presented images against the corresponding subject-level prediction derived from this procedure. As the figure shows, this simple procedure provides a remarkable fit to the individual data, yielding a correlation with the observed values of  $r(26) = 0.88$  for negative images, and  $r(26) = 0.80$  for neutral images ( $p < 0.001$  for both).

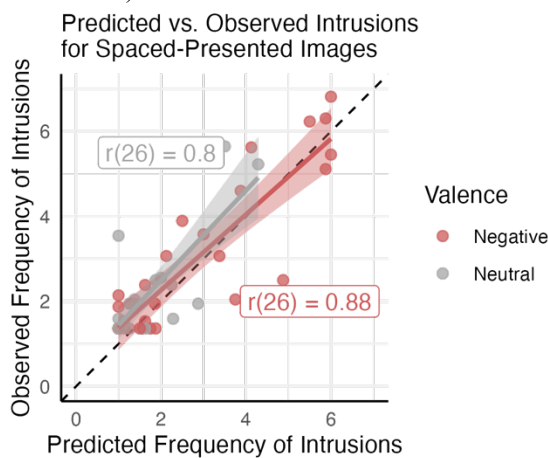


Figure 7: Predicted vs. observed frequencies of intrusions for spaced-presented images. Points represent participants.

## Discussion

Prior to the experimental component of our study, two predictions could be made through our simulations: (1) that the perceived frequency of intrusions for spaced-presented images would be approximately 1.36 times more than massed-presented ones, and that (2) emotional distress of the image intrusions would be the same across massed and spaced presentations for negative images.

The experimental results corroborated the model predictions: we demonstrated that the sequence in which images are presented (massed vs. spaced) had an effect on memory retention; specifically, during the 24 hours after first exposure to the negative images, the frequency of intrusions

in the massed conditions were lower than those in the spaced conditions. Thus, in terms of traumatic memory, massed reactivations in the short term may result in less retention of the memory in the long term.

Reactivation of trauma memories is not at all a novel concept in PTSD treatment. Exposure therapy, for example, aims to address the anxiety and avoidance typically seen in PTSD and alter reactivity towards these triggering memories; this kind of therapy focuses on reactivating trauma memories and gradually associating triggers with new, safe responses and meaning. However, this occurs after intrusive memories have already emerged and become persistent. Massing the reactivations and retrievals of these memories may constitute a complementary intervention, one that focuses on the root of the issue by regulating the availability of intrusive memories before they take hold.

Despite our promising results, we acknowledge our relatively small ( $N = 27$ , young, educated undergraduates) and homogenous sample size, which may not be representative of most PTSD clinical populations. Furthermore, the time course of our study is much more compressed compared to the typical time course of PTSD symptoms, which might unfold over weeks or months. Thus, while our paradigm might be representative of specific real-life applications (e.g., online content moderators experiencing PTSD from repeated viewings of traumatic materials), it might not generalize to most cases.

The limited time course of our experiment might also be a potential root cause for the lack of a significant difference between the distress caused by intrusions of massed- vs. spaced- negative images. While this was indeed a prediction of our model, it is possible that, over longer times or over a larger number of re-encodings, a significant difference would have emerged. In fact, both of the models that inspired our experiment (Larue et al., 2018; Smith et al., 2021) do predict that, with repeated retrievals of traumatic memories in non-traumatic contexts, the distress associated with the memory should eventually decline. Thus, future studies should examine more carefully the interactions between intrusive memory distress and re-encoding spacing.

These limitations notwithstanding, this current study demonstrates the potential of applying cognitive models to mental health, an approach known as computational psychiatry (Montague et al., 2012). The current clinical understanding of PTSD is rooted in associative learning and conditioning frameworks; our findings, in contrast, demonstrate the importance of applying declarative memory models and principles to improve the design of more effective trauma management and therapeutic strategies for intrusive memories in PTSD. By inverting the spacing effect, we may be able to address what has traditionally been overlooked in trauma management, which is how the critical period immediately after potentially traumatic events should be addressed.

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