Memory augmentation with an adaptive cognitive interface

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Abstract

What we remember reflects both what we encounter, such as the intrinsic memorability of a stimulus, and our internal attentional state when we encounter that stimulus. Our memories are better for memorable images and images encountered in an engaged attentional state. Here, in an effort to modulate long-term memory performance, we manipulated these factors in combination by selecting the memorability of presented images contingent on individuals' natural fluctuations in sustained attention. Can image memorability and attentional state be strategically combined to improve memory? Are memorable images still well-remembered during lapses in sustained attention, and conversely, can attentive states rescue memory performance for forgettable images? We designed a procedure to monitor participants' sustained attention dynamics on the fly via their response time fluctuations during a continuous performance task with trial-unique scene images. When high or low attentional states were detected, our algorithm triggered the presentation of high or low memorability images. Afterwards, participants completed a surprise recognition memory test for the attention-triggered images. Results demonstrated that memory performance for memorable items is not only resistant to lapses in sustained attention, but also that memory cannot be further improved by encoding memorable items in engaged attentional states. On the other hand, memory performance for low memorability images can be rescued by attentive encoding states. In sum, we show that both memorability and sustained attention states can be leveraged in real time to maximize memory performance. This approach suggests that adaptive cognitive interfaces can tailor *what* information appears *when* to best support overall memory performance.

Keywords: attentional dynamics, memorability, real-time triggering, recognition memory

As we proceed through everyday life, we encounter a diverse range of visual information in a variety of attentional states. But only some fraction of that information is later remembered. Recent research has revealed that both *what* specific image we view and *when* we see it (namely, how attentive we are when we see it) predict the mnemonic fate of a stimulus. For example, an inherently memorable image is much more likely to be remembered (Bainbridge et al., 2013; Isola et al., 2011). An image encountered in an attentive state is also much more likely to be remembered (Chun & Turk-Browne, 2007; deBettencourt et al., 2018; Wakeland-Hart et al., 2022). These findings suggest that both stimulus memorability and an individual’s attention can be leveraged to improve memory.

The *intrinsic memorability* of an image refers to the likelihood that one will correctly remember having seen it previously (Bainbridge et al., 2013; Isola et al., 2011). Memorability is highly reliable across participants, even when controlling for visual features (e.g., spatial frequency, color; Bainbridge, 2020; Isola et al., 2014) or stimulus category (Kramer et al., 2023). New work has found that abstract visualizations (Borkin et al., 2013; Roberts et al., 2023), words (Tuckute et al., 2018), drawings (Han et al., 2023), paintings (Davis & Bainbridge, 2023), and even dance moves (Ongchoco et al., 2023) are reliably remembered or forgotten across individuals. The intrinsic memorability of an image even predicts later recognition over longer timescales (e.g., when tested after a one-week retention interval; Goetschalckx et al., 2018), predicts memory in naturalistic museum settings (Davis & Bainbridge, 2023), and captures memory performance in children as young as four years old (Guo & Bainbridge, 2023). Intrinsic memorability, therefore, is widely considered to be a feature that is inherent to a stimulus, and that is predictive of memory across a range of contexts and populations. However, it remains an open question whether and how memorability might be influenced by one’s internal state.

Our internal states—such as how attentive we are to a task at hand—vary considerably over time. Attention fluctuations can be measured with subjective approaches, such as intermittent thought probes (e.g., Smallwood et al., 2008) and continuous self-report ratings (e.g., Song et al., 2021), or with objective approaches, such as response times (RTs; e.g., Corriveau, Chao, et al., 2024; Corriveau, James, et al., 2024; deBettencourt et al., 2018), pupillary responses (e.g., Keene et al., 2022), and neural measures (e.g., deBettencourt et al., 2021; Jones et al., 2023). Specifically, prior work using continuous performance tasks have shown that *sustained attention* during a task correlates with RTs, such that slower RTs reflect higher attention (Cheyne et al., 2006, 2009; deBettencourt et al., 2018, 2019; Esterman et al., 2013; Manly et al., 1999; Robertson et al., 1997; Zhang & Rosenberg, 2023). These attentional states influence memory performance, regardless of which stimulus appears. For example, memory performance is better when attention is more engaged during both memory encoding (Chun & Turk-Browne, 2007; deBettencourt et al., 2018, 2021; Wakeland-Hart et al., 2022) and memory retrieval (Madore et al., 2020; Madore & Wagner, 2022).

Although memorability is specific to a stimulus (e.g., an image), attentional states are comparatively idiosyncratic. That is, the memorability of a given image represents an aggregate factor that can be measured ahead of time through prior studies (e.g., Isola et al., 2011) or estimated via artificial neural networks (e.g., ResMem; Needell & Bainbridge, 2022), whereas sustained attention differs both between people and within a person over time. Prior research has shown that when memorability and sustained attention are manipulated separately, they both predict unique sets of variance in later memory performance (Wakeland-Hart et al., 2022). This opens up the possibility of leveraging both factors simultaneously to maximize memory performance. Therefore, the challenge lies in creating a cognitive interface that can make use of both the stable, population-level measure of an image's memorability, while at the same time considering an individual's moment-to-moment changes in sustained attention. Recent studies have demonstrated how response times (RTs) can be used as an objective, real-time index of sustained attention to adaptively modify experiment parameters on the fly. In deBettencourt et al. (2018), participants classified scene images, the category of which—unbeknownst to them—varied depending on their real-time sustained attention. This study revealed that using RTs to index sustained attention was a viable way to predict subsequent memory on an image-by-image basis. More importantly, this work also demonstrated the feasibility of creating cognitive interfaces that dynamically adapt to the user's behavior on each trial.

In the current study, we aimed to create an adaptive cognitive interface that could track an individual's sustained attention, then leverage that information to dynamically present memorable or forgettable images, all in real time. By strategically inserting memorable or forgettable images when sustained attention is waxing and waning, one can not only maximize memory performance in ideal conditions, but can perhaps also 'rescue' memory for low memorability images by inserting them when attention is high. Here, we explored whether real-time performance tracking could be used to create adaptive cognitive interfaces whereby images with known memorability characteristics are strategically presented to influence later memory performance. In other words, we asked: Can we modulate participants' recognition memory performance by presenting memorable or forgettable images depending on their attentional state?

Methods

The procedures and materials for this study were approved by the Institutional Review Board (IRB) at the University of Chicago. All data, analysis code, experiment programs, and other materials are made available on the Open Science Framework (OSF; https://osf.io/9vc5a/).

Participants

The number of participants per condition was determined *a priori* using G*Power v3.1.9.6 (Faul et al., 2007) with a power analysis based on the reported effect of attentional state on subsequent memory performance from prior work (Experiment 3 in Wakeland-Hart et al., 2022). The parameters were as follows: one-group linear bivariate regression, two-tailed test, estimated slope = .18, $\sigma_x = 1$, $\sigma_y = .34$, $\alpha = .05$, power = .8, indicating a minimum sample size of 23 participants in each group. Because two groups were to be collected ('congruent', i.e., pairing high attention states with high memorability images, and conversely, 'incongruent'), the minimum sample size was doubled to 46, while a target sample size was set at 64 to increase our chances of finding true effects if they exist.

In the end, a total of 68 participants aged 18-35 were recruited using the University of Chicago SONA undergraduate recruitment system and completed the study in the laboratory. Participants were assigned to one of two experimental conditions (Congruent or Incongruent) in alternating order. All participants were compensated for their time with either half a course credit or $5 USD, provided written informed consent, and had self-declared normal or corrected-to-normal color vision, no prior major head injuries, and no diagnosis of psychiatric or neurological disorders. Data from four participants were excluded while data collection was ongoing: two participants switched the response mapping on the continuous performance task, one participant had continuous performance task data that was > 3 standard deviations (*SD*s) below the group average up to that point, and one participant had memory task performance that was > 3 *SD*s below the group average up to that point. The four excluded participants were replaced to ensure condition groups of an equal size. The final sample size used for analyses was 64, split evenly between two groups (Congruent and Incongruent). Both groups had similarly aged participants (Congruent: M_{age} = 20.80, SD_{age} = 3.86; Incongruent: M_{age} = 19.70, SD_{age} = 1.36), with similar sex ratios (Congruent: 17 female, 15 male; Incongruent: 20 female, 12 male).

Apparatus

The entire experiment was displayed on a 15” MacBook Pro laptop screen with a resolution of 1920x1080p running at 60Hz refresh rate, while the experiment was presented using MATLAB (v. 2022b; *Matlab*, 2022) and Psychtoolbox (v. 3.0.18; Kleiner et al., 2007). Participants were seated approximately 61 centimeters from the screen. Image stimuli subtended approximately 7.25° of visual angle on the screen with a black fixation dot subtending approximately 0.6°, centrally presented and overlayed on top of stimuli images during the continuous performance task (but absent during the memory test).

Procedure

During the experiment, participants completed two tasks: first, a continuous performance task with trial-unique images, and then a recognition memory task to assess which images were later remembered (**Figure 1**). The continuous performance task utilized a real-time triggering protocol which allowed us to tailor which images were presented to participants when, by tracking their attentional state in the moment and leveraging memorability scores collected previously.

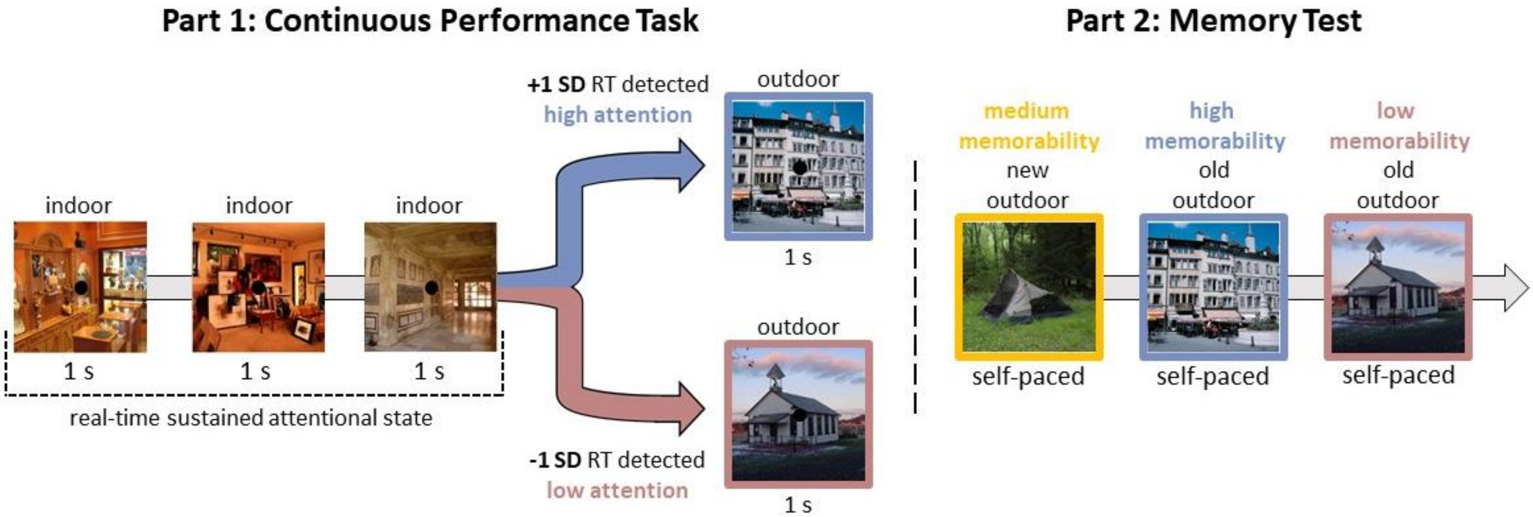

Figure 1. Experiment procedure for participants in the congruent condition. When *high* attention was detected in this condition, a high memorability image was triggered. Conversely, when *low* attention was detected in this condition, a low memorability item was triggered. The opposite occurred in the incongruent condition. Note that in all cases, triggered images belonged to the infrequent category. During the recognition memory test, all of the old, infrequent-category images were presented (both high and low memorability, indicated here by blue and red borders, respectively), as well as an equal number of new images (medium memorability, indicated here by a yellow border). Images without borders here indicate trials in which the memorability was unconstrained. During the actual experiment tasks, images did not have borders.

Continuous performance task

The continuous performance task was designed to elicit and allow for the measure of sustained attentional fluctuations by presenting a stream of scene images. On each trial, a single, trial-unique image was centrally presented on a gray background overlayed with a black fixation dot for 1000 ms. Participants categorized each image as indoor or outdoor by pressing the ‘J’ or ‘H’ keys on a keyboard (counterbalanced across participants). The fixation dot turned white after a response was recorded. Trials progressed regardless of whether a response was made, and there was no interstimulus interval. The proportion of indoor/outdoor images were imbalanced to better elicit natural fluctuations in sustained attention. At least 90% of the images belonged to one ‘frequent’ category (either indoor or outdoor, counterbalanced across participants). The remaining images (at most 10%) belonged to the other stimulus category (i.e., the ‘infrequent’ category, either outdoor or indoor). Before starting the main continuous performance task, participants practiced 10 trials repeatedly until they reached 90% accuracy using different images that were not repeated in the main task. There was no mention of a later memory test or of any instruction to remember the images for later. The continuous performance task went on without any breaks until all 500 trials were completed, for a total duration of 8 minutes and 20 seconds.

Image Stimuli

This experiment used a set of 1,100 scene images from the Scene UNderstanding database (SUN; Xiao et al., 2010). These images depict a wide variety of representative real-world scenes from 281 subcategories, with 550 indoor scenes and 550 outdoor scenes, and were the same images used in prior related work (deBettencourt et al., 2018). We removed 3 images from the set (1 indoor and 2 outdoor images) due to the presence of salient features, such as prominent faces or text. All images were cropped to be square, resized to 450x450 pixels, and were presented in full color.

Memorability

The intrinsic memorability of each image was determined in prior work (Wakeland-Hart et al., 2022). In that study, 706 online participants completed a continuous recognition test in which a stream of images appeared and their task was to detect repeated items (see Bainbridge, 2019). A response was considered a ‘hit’ when a subject correctly identified an image as a repeat, or a ‘false alarm’ when they incorrectly indicated that a novel image was a repeat. The memorability of each image was operationalized as the average corrected recognition (CR) rate by subtracting the mean false alarm rate from the mean hit rate across participants.

We began by sorting all images based on their CR rate as reported by Wakeland-Hart et al. (2022) and then selecting the 50 highest memorability and 50 lowest memorability images from each category, indoor and outdoor. To reduce any disproportionate representation of specific image subcategories (e.g., office, bar), we retained only one image per subcategory in each of the high and low memorability sets. For example, the high memorability indoor set could only contain one image of an office. If, upon first pass, the high memorability indoor set contained more than one image per subcategory (e.g., two images of offices), we retained the image with the most extreme memorability score. We replaced the other image(s) with the next most or least memorable item from a novel subcategory. As a result, high and low memorability image sets could have some overlap in subcategories, but no specific subcategory was overrepresented in either set. In the end, high memorability images ranged in CR score from 0.75 to 0.95, whereas low memorability images ranged in CR score from 0.26 to 0.56.

We also selected an equal number of indoor and outdoor images of middle memorability (100 images total per scene category, $0.56 < CR < .75$) to serve as new items during the surprise recognition memory test. These middle-memorability images were pseudorandomly selected using a similar procedure as described above, such that all subcategories were roughly equally well-represented.

To ensure low-level features did not significantly differ between high and low memorability images, we used the Natural Image Statistical Toolbox (Bainbridge & Oliva, 2015). We did not observe any reliable differences in color or spatial frequencies ($ps \geq .5$) between high and low memorability images. Images and their corresponding memorability scores are available at https://osf.io/6uc48/ (Wakeland-Hart et al., 2022), while a list of the specific images used in this experiment can be found at https://osf.io/9vc5a/.

Real-time triggering based on attentional state

The goal of the real-time triggering procedure used in this experiment was to provide an adaptive encoding environment for each participant that integrated their natural fluctuations in attentional state with the intrinsic memorability of the images they were observing. The continuous performance task provided response times (RTs) that were used to track each participant's attentional state fluctuations in real time. For a trial i, we first calculated and subtracted the linear trend in RTs (trials 1 to i), to remove general effects of fatigue or practice. Then, we calculated a real-time measure of attentional state, x_i, based on the trailing window average over the detrended RTs from the three most recent trials (trials i-2, i-1, i). We defined a predetermined threshold, ± 1 standard deviation (σ_i) from the mean (μ_i), both of which were calculated over detrended trials 1 to i. When the attentional state (x_i) exceeded our threshold (σ_i), an image from the infrequent category was triggered (i.e., either an indoor or outdoor scene) for trial i+1. Thus, images triggered by especially slow RTs ($x_i > \sigma_i - \mu_i$) were encoded during high attention states, whereas images triggered by especially fast RTs ($x_i < \sigma_i - \mu_i$) were encoded during low attention states. We also required that the three preceding trials (i-2, i-1, i) were correct frequent-category responses and that $i > 50$ to ensure no confounds due to lack of practice.

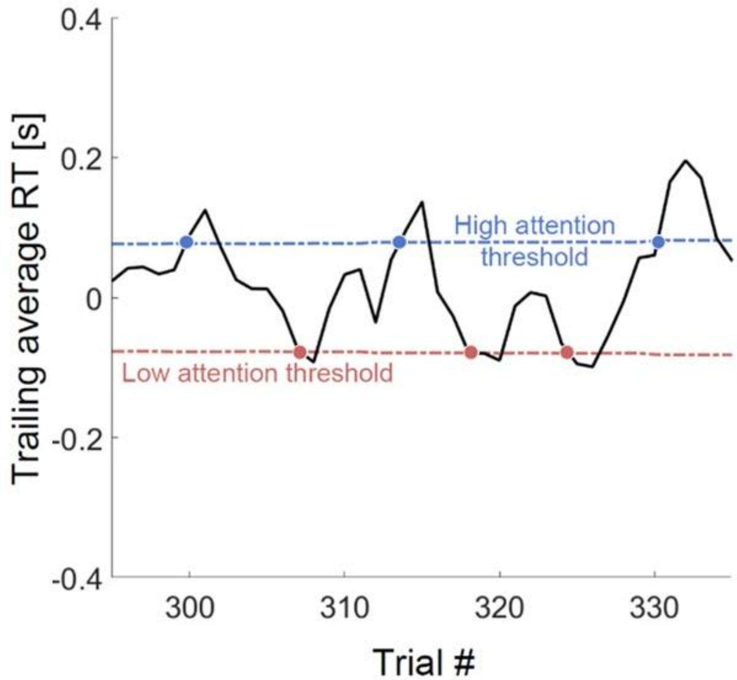

Figure 2. An illustration of the attention triggering procedure with example data showing real-time event triggering dependent on states of high and low attention, as calculated based on trailing average RT. Dotted lines in blue and red represent the ±1 *SD* threshold used to indidicate states of high or low sustained attention, respectively. Blue and red dots correspond to trials when a participant's sustained attention is detected as being high or low, respectvely, thus triggering an infrequent category image on the subsequent trial.

Experimental conditions

Participants were assigned to one of two experimental conditions in an alternating manner: Congruent and Incongruent. If a subject was in the Congruent condition, attention state and image memorability were matched such that, when a participant was in a high attention state, a high memorability image from the infrequent category was inserted. If they were in the Incongruent condition, attention state and image memorability were mismatched such that, when a participant was in a high attention state, a low memorability image from the infrequent category was inserted. Critically, for both conditions, while frequent-category images could have any memorability score, infrequent-category images were manipulated to be either high or low memorability only. The memorability of these infrequent-category images depended on the attentional state that triggered the infrequent trial, as well as the participant’s congruency condition assignment.

Memory task

Immediately following the continuous performance task, participants performed a surprise image recognition memory test (self-paced, approximately 8 minutes to complete) consisting of all infrequent-category images seen during the continuous performance task (‘old’ images). There was also an equal number of new images randomly selected from the larger collection of 100 middle-memorability images for the same scene category as the ‘old’ images. No images from the frequent category in the encoding phase were presented during the memory task. Images were presented in a random order. Participants were instructed to indicate their memory and confidence that each image had appeared in the continuous performance task on a scale of 1–4: ‘1’ indicated high confidence that the image was new, ‘2’ was low confidence that the image was new, ‘3’ was low confidence that the image was old, and ‘4’ indicated high confidence that the image was old. Participants were encouraged to use the entire response scale. High-confidence old responses (i.e., responses of ‘4’) were later taken to indicate that an item was considered previously studied, whereas all other responses were taken to indicate that an item was not seen before (deBettencourt et al., 2018; Kim et al., 2014; Turk-Browne et al., 2006; Wagner et al., 1998; Wakeland-Hart et al., 2022). After each response, the image remained on the screen along with the indicated confidence rating for an additional 500ms before the next image appeared; there was no interstimulus interval.

Statistical approach

A' (A-prime; Stanislaw & Todorov, 1999) was used to assess recognition memory performance due to its nonparametric assumptions. These nonparametric qualities are robust to violations of normality that are likely to be present when studying the extremes of memorability and sustained attention distributions. A' was calculated from the hit rate of triggered (‘old’) items on the recognition test (separately for images encoded in high and low attention states) and the false alarm rate for new items.

To examine memory performance across conditions, a mixed-effects logistic regression was formed using the *lme4* package (v. 1.1-34; Bates et al., 2015) for *R* (v. 4.3.2; R Core Team, 2020), employing the Satterthwaite adjustment to degrees of freedom. Attention (high, low) and memorability (high, low) were entered as binary predictors regressed onto A' with a subject-level random factor included as well:

$$A' \sim Attention\ *\ Memorability\ +\ (1\ |\ Participant)$$

To compare the relative contributions of attention and memorability in predicting later memory performance, a contrast was conducted using the *multcomp* package (v. 1.4-25; Hothorn et al., 2023). Between-group comparisons were then conducted via the *emmeans* package (v. 1.8.9, Lenth et al., 2023), while effect sizes (Cohen’s *d*) and their 95% confidence intervals were determined with 10,000 bootstraps via the percentile method in the *rstatix* package (v. 0.7.2, Kassambara, 2021). Bayes factors were calculated using the *BayesFactor* package (v. 0.9.12-4.5; Morey et al., 2011), enlisting a default Jeffreys-Zellner-Siow (JZS) prior with a Cauchy distribution (center = 0, r = .707). This package compares the fit of various linear models. In the present case, Bayes factors for the alternative (BF_{10}) are in comparison to null models containing participant as a random effect. Bayes factors for interactions are relative to models containing both main effects. Interpretations of Bayes factors follow the conventions of Lee and Wagenmakers (2013). Bayes factors in favor of the alternative (BF_{10}) or null (BF_{01}) models are presented in accordance with each preceding report of NHST analyses (i.e., based on a $p < .05$ criterion) such that $BF \geq 1$.

Finally, receiver operating characteristic curve (ROC) analyses were also conducted using the ROC Toolbox (Koen et al., 2017) for MATLAB, treating response decisions as continuous based on confidence ratings rather than as binary old/new decisions. Due to an insufficient number of trials in each condition per participant, however, we were unable to compare results statistically. The pattern of results based on ROC analyses, however, matched the results presented here based on A' (see the Supplemental Materials for more details).

Results

The goal of this study was to determine whether memory performance can be improved by first detecting real-time fluctuations in sustained attention and then using that information to present specific images with predetermined levels of intrinsic memorability. We expected both attention and memorability to each significantly predict later memory performance. We also reasoned that inserting high memorability images could maximize performance when attention was high and rescue performance when attention was low. Analogously, we predicted that inserting low memorability images would minimize performance when attention was low, but when inserted when attention was high, may allow for memory performance for these impoverished items to be rescued.

Verifying the adaptive cognitive interface

We first examined whether real-time triggering successfully captured fluctuations in sustained attention. Sustained attention was operationalized as the real-time RTs in the continuous performance task, after detrending and averaging over a trailing window. Indeed, our algorithm successfully differentiated states of sustained attention, with quicker response times on low attention triggered trials (mean centered RT = -0.159), and slower response times on high attention triggered trials (mean centered RT = 0.182; see **Figure 3A**).

Next, we examined the memorability of the images that appeared contingent to extreme attentional states. Memorability was operationalized as the corrected recognition (CR) scores for these images, as determined by testing with a separate sample of participants (see Methods). As can be seen clearly in **Figure 3B**, our algorithm successfully displayed extremely low (average CR = 0.469) or extremely high (average CR = 0.834) memorability images, dependent on attentional state and congruency group assignment.

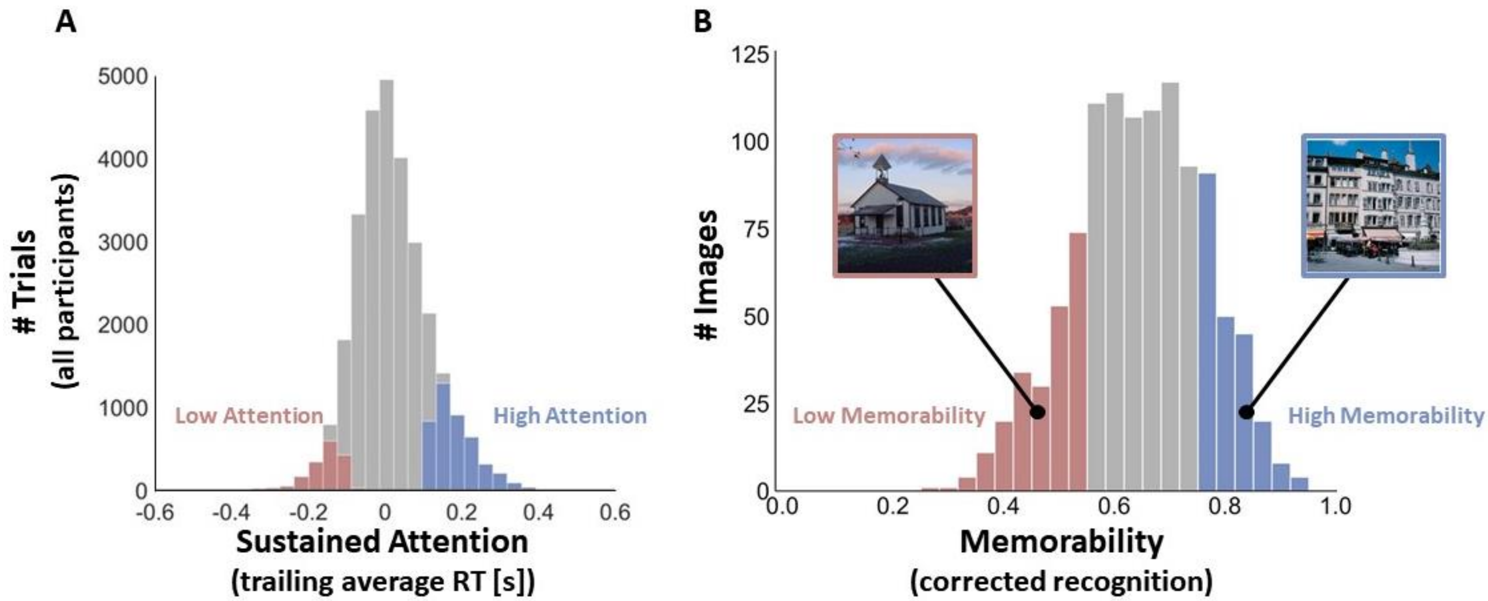

Figure 3. (A) Histogram of all trials from the encoding phase with high attention trials in blue and low attention trials in red, indicating successful implementation of the attention manipulation for slow and fast RTs, respectively. **(B)** Histogram of memorability scores for all scene images in the stimulus set. Triggered images with low memorability are depicted in red, while triggered images with high memorability are depicted in blue. Example high and low memorability stimuli are displayed.

Memory performance

A mixed-effects logistic regression was used to assess the effects of image memorability and sustained attention on later memory performance. There were significant main effects of both attention, $\beta = .49$, $SE = .02$, $t(118.22) = 2.09$, $p = .039$, $BF_{10} = 1.67$, and memorability, $\beta = .81$, $SE = .02$, $t(118.22) = 3.49$, $p < .001$, $BF_{10} = 1{,}565$ on memory, such that higher attention and intrinsic memorability predicted better memory performance (see **Figure 4A**). The interaction effect, representing the effect of Congruency group, was nonsignificant, $\beta = -.28$, $SE = .04$, $t(62) = 0.77$, $p = .446$, $BF_{01} = 2.52$. A contrast to compare the relative contributions of attention and memorability in predicting later memory performance revealed that the variance explained by the two factors were not reliably different, $z = -1.58$, $SE = 0.02$, $p = .114$.

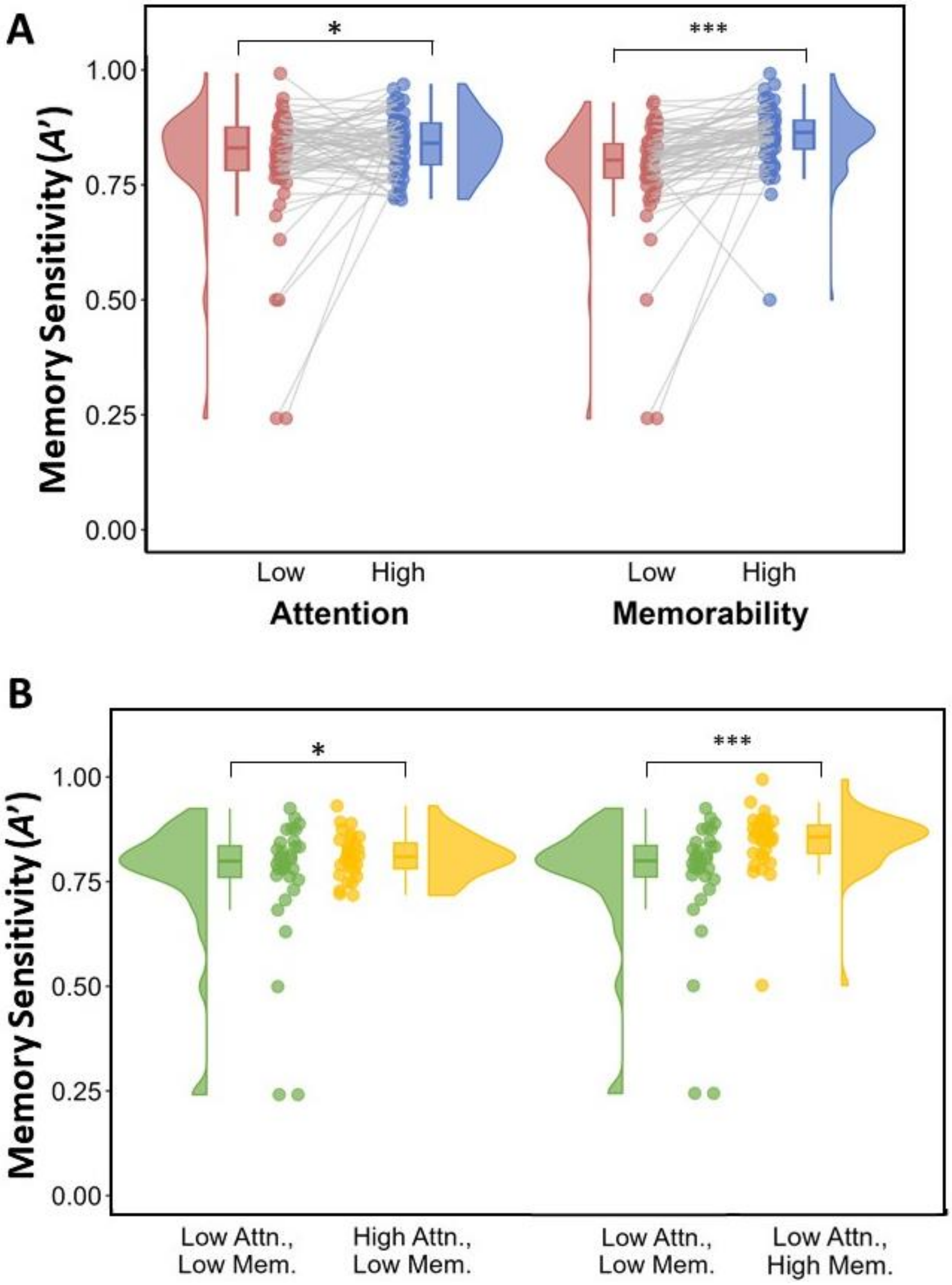

Figure 4. Memory performance (A') modulations as a function of sustained attention and memorability. **(A)** Memory performance benefits for high relative to low levels of both attention and memorability within-subject, including individual data points for each participant connected with a line to show their change in performance, along with smoothed distributions and box-plots. **(B)** Between-subjects contrasts demonstrating effects of interest, namely that high attention ‘rescues’ performance for low memorability images (left), and that high memorability images elicit increased memory performance, even when attention is low (right).

Next, the effects of high and low levels of attention and memorability were examined between groups. Planned comparisons revealed that memory performance was significantly greater for high memorability images relative to low memorability images when encoded under both high attention, $t(118) = 2.29$, $p = .024$, $d = 1.01$, CI_{95} [0.51, 1.67], $BF_{10} = 160$, and low attention, $t(118) = 3.49$, $p < .001$, $d = 0.67$, CI_{95} [0.27, 1.08], $BF_{10} = 4.98$ (**Figure 4B**, right), revealing that the effects of memorability are relatively immune to fluctuations in sustained attention. Memory performance for high memorability items did not differ as a function of sustained attention state, $t(118) = 0.89$, $p = .374$, $d = 0.31$, CI_{95} [-0.19, 0.75], $BF_{01} = 2.06$, suggesting that high memorability itself can keep performance levels high, even when attention wanes (see **Table 1**). However, when testing low memorability (i.e., forgettable) images, memory was better for items encoded under high attention, $t(118) = 2.09$, $p = .039$, $d = 0.43$, CI_{95} [-0.02, 0.77], $BF_{10} = 0.88$, suggesting that memory for forgettable images can be rescued if they are encoded in an attentive state (**Figure 4B**, left).

Table 1

Descriptive Statistics for Memory Performance Across Groups and Conditions

Condition	**Attention**	**Memorability**	***A′***		**Hit Rate**		**False Alarm Rate**		**Corrected Recognition**	
			M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Congruent	High	High	.87	.06	.54	.20	.03	.04	.51	.20
	Low	Low	.76	.16	.31	.20			.28	.19
Incongruent	High	Low	.81	.05	.38	.17	.04	.05	.33	.15
	Low	High	.84	.08	.51	.21			.46	.19

Note. All performance metrics reported here refer to data from the memory test in our current study. Corrected recognition refers to hit rate minus false alarm rate.

Thus, recognition memory performance for high memorability images was consistently better than for low memorability images and was unaffected by attentional state at encoding. Memory for low memorability images, on the other hand, was better when they were encoded in states of engaged attention. In other words, high memorability can improve memory for images encountered in disengaged attentional states, while engaged attention can improve memory for low memorability images. Encoding highly memorable images in highly attentive states, however, does not confer additional benefits for memory.

Discussion

In the current study, we designed an adaptive cognitive interface that strategically inserted specific images contingent on real-time detection of cognitive states. That is, we inserted high or low memorability images when participants were attentive or inattentive. Our goal was to directly manipulate the interplay between internal states (in this case, sustained attention) and external stimulus-based factors (in this case, intrinsic memorability). We measured sustained attention in real time via response times on a continuous performance task. When a high or low attention state was detected, the algorithm triggered an image on the subsequent trial. The triggered image was either high or low memorability, depending on whether the participant was assigned to the congruent or incongruent condition. We observed that both high attention and high intrinsic memorability benefitted memory performance. In sum, we created adaptive encoding phases, whereby later memory performance could be examined to determine the maximally efficient combination of attention and memorability at encoding.

Memorable and forgettable images were differentially susceptible to sustained attentional state. Although there was no additive benefit of encoding memorable images while in a highly attentive versus a low attentive state, forgettable images were better remembered when encoded in a highly attentive state. That is, when tasked with trying to remember an image that is known to be forgettable, it helps to be in an attentive state. So, while the intrinsic memorability of an image is an important determinant of later memory performance, there is still a memory benefit in trying to pay attention: Performance can be rescued when to-be-remembered stimuli are forgettable.

In contrast to the different effects of attention on memory for memorable and forgettable images, the intrinsic memorability of an image impacted memory regardless of attentional state. Memorable images were better remembered than forgettable ones when participants were both engaged and disengaged. The benefits of encoding high memorability images, therefore, are immune to lapses in attention.

We found that both sustained attentional state and intrinsic memorability influence later recognition memory performance. Interestingly, however, attentional state did not significantly affect memory for highly memorable images. Why? One possibility is that the locus of control for later recognition of high memorability images is not held by the observer but is rather largely pre-determined by features of the stimulus itself. Memory performance for memorable images can therefore remain robust to attention lapses. Another possibility is that our attention-triggering algorithm did not sample the most extreme attentional states. Because we required the three trials preceding any triggered image to be correct frequent-category trial responses, we did not present triggered trials during lapses that were catastrophic enough to cause errors on frequent-category image classifications. Potentially supporting this notion, highly memorable images were numerically (but not significantly) better remembered when encoded in states of high relative to low attention.

Future work varying attentional-state-dependent triggering criteria and encoding task features (such as the degree to which they facilitate engaged vs. lapsing attention) can further characterize the relative strength of memorability and attentional state as predictors of subsequent memory. Later interfaces could be even more personalized, with specific tailoring of the image content to the participant to maximize its memorability. A triggering model that incorporates task-specific information or a more nuanced attention measure (such as one measured from the brain) could enhance our ability to elicit improved memories. However, one important factor to balance when utilizing an alternate sustained attention measure is that there must be sufficient moments of extremely high or low attention to elicit enough triggered trials.

Here, we have shown that people's memory performance can be altered without any intentional encoding or cognitive strategy (e.g., chunking, drawing). By simply taking advantage of natural fluctuations in attention and strategically presenting specific materials, we can ensure the best performance possible. This study supports both memorability as an intrinsic stimulus characteristic, and attentional state as being influential to memory encoding. In other words, we show how memorability and attention jointly contribute to episodic remembering and therefore should both be considered when developing contemporary models of memory.

In the laboratory, this new technology allows for not only the tailoring of experiments and digital experiences to each individual, but also for the customization of parameters on a moment-by-moment basis, dependent on the individual's performance or feedback. Such tools can be used to examine the interplay of seemingly any cognitive process, allowing for the cross-examination of population-level phenomena with idiosyncratic cognitive and neural mechanisms. Employing such a tool in the present case, we were able to characterize the interplay of individual attention and image memorability on later memory performance and demonstrate that each factor is able to rescue memory when the other factor is diminished.

Adaptive cognitive interfaces also have numerous practical and translational applications. For example, our current approach could be employed in educational settings to present the least memorable concepts when students are most attentive (Guo & Bainbridge, 2023). For example, when learning a foreign language, memorable or forgettable vocabulary could be strategically presented contingent to the learner's attentional state. This approach could also be used to scaffold memory and learning for populations that have impairments in memory (e.g., Alzheimer's disease) or attention (e.g., attention-deficit hyperactivity disorder). Importantly, our approach uses measures that are relatively easy to capture—attention is simply measured by response time, while image memorability can be estimated in advance using neural networks (Needell & Bainbridge, 2022), making such innovations feasible to incorporate into any system.

Conclusion

Recent work has established the contributions of two major factors that influence what information is likely to be remembered: intrinsic memorability and sustained attention. While both factors are known to influence memory individually, it was still unclear how their *combination* might alter memory, and whether they could be leveraged together to maximize overall performance. Here, we developed and validated an adaptive cognitive interface—customized for each participant on the fly—that allowed for consideration of both *what* information is presented and *when* to show it (based on intrinsic memorability and sustained attention, respectively). In so doing, we have shown that when participants are inattentive, encoding of highly memorable images reliably improves memory performance relative to forgettable images, despite participants' lack of focus. Memory for forgettable images, on the other hand, can be 'rescued' if shown when participants are in states of high attention. As a result, we have demonstrated that natural fluctuations in participants' attentional states and the intrinsic memorability of to-be-remembered stimuli can be strategically combined to bolster memory in any given situation.

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