



# Judgments of learning reveal conscious access to stimulus memorability

Joseph M. Saito<sup>1</sup> · Matthew Kolisnyk<sup>2</sup> · Keisuke Fukuda<sup>1,3</sup>

Accepted: 25 July 2022  
© The Psychonomic Society, Inc. 2022

## Abstract

Despite the massive capacity of visual long-term memory, individuals do not successfully encode all visual information they wish to remember. This variability in encoding success has been traditionally ascribed to fluctuations in individuals' cognitive states (e.g., sustained attention) and differences in memory encoding processes (e.g., depth of encoding). However, recent work has shown that a considerable amount of variability in encoding success stems from intrinsic stimulus properties that determine the ease of encoding across individuals. While researchers have identified several perceptual and semantic properties that contribute to stimulus memorability, much remains unknown, including whether individuals are aware of the memorability of stimuli they encounter. In the present study, we investigated whether individuals have conscious access to the memorability of real-world stimuli while forming self-referential judgments of learning (JOL) during explicit memory encoding (Experiments 1A–B) and when asked about the perceived memorability of a stimulus in the absence of attempted encoding (Experiments 2A–B). We found that JOLs and perceived memorability estimates (PME) were consistent across individuals and predictive of memorability, confirming that individuals can access memorability with or without stimulus encoding. At the same time, access to memorability was not comprehensive. We found that individuals unexpectedly remembered and forgot consistent sets of stimuli as well. When we compared access to memorability between JOLs and PMEs, we found that individuals had more access during JOLs. Thus, our findings demonstrate that individuals have partial access to stimulus memorability and that explicit encoding increases the amount of access that is available.

**Keywords** Visual memory · Judgment of learning · Metamemory

Visual long-term memory has a massive capacity that allows individuals to store a great deal of visual information with high levels of precision (Brady et al., 2008; Brady et al., 2013; Standing, 1973). However, individuals do not successfully encode all visual information they encounter in everyday life. These memory encoding failures have been mainly attributed to moment-to-moment fluctuations in cognitive states (e.g.,

Fukuda & Woodman, 2015; Noh et al., 2014; Wagner et al., 1998) and encoding processes (e.g., Bower & Karlin, 1974; Craik & Lockhart, 1972; Ovalle-Fresa et al., 2021; Sundby et al., 2019; Tozios & Fukuda, 2019) that vary across individuals and learning episodes. However, more recent work has illustrated that memory encoding success for a given visual stimulus covaries across individuals and learning episodes such that some visual stimuli are consistently remembered while others are consistently forgotten. Such consistency in memory performance has been used to suggest that visual stimuli possess intrinsic properties that determine their ease of encoding independently of individual-specific encoding variables (Bainbridge et al., 2013; Isola et al., 2014).

Given the ubiquity of this observed stimulus memorability across different stimuli and tasks (Bainbridge et al., 2013; Broers et al., 2018; Bylinskii et al., 2015; Isola et al., 2014; Madan, 2021; Madan et al., 2017; Xie et al., 2020), it is critical to identify its determinant factors. While studies have identified a number of perceptual, social, and semantic

---

Joseph M. Saito and Matthew Kolisnyk contributed equally to this work.

✉ Keisuke Fukuda  
keisuke.fukuda@utoronto.ca

<sup>1</sup> Department of Psychology, University of Toronto, 100 St. George Street, Toronto, ON M5S 3G3, Canada

<sup>2</sup> Department of Psychology, Western University, 1151 Richmond Street, London, ON N6A 3K7, Canada

<sup>3</sup> Department of Psychology, University of Toronto Mississauga, 3359 Mississauga Rd, Mississauga, ON L5L 1C6, Canada

factors that contribute to stimulus memorability, a large portion remains unexplained (Bainbridge et al., 2013; Bainbridge et al., 2017; Lin et al., 2021; Xie et al., 2020). Such unexplained factors demonstrate the elusiveness of stimulus memorability to scientists, but does this imply that stimulus memorability is also elusive to individual observers, such that they lack awareness of what stimuli are memorable? To answer this, Isola et al. (2014) presented participants with sequences of random images and asked them to rate how memorable each image was. When participants' memory for these images was assessed with a surprise recognition test afterwards, the perceived memorability estimates (PMEs) reported by participants initially did not reliably predict the veridical memorability established by the subsequent recognition test. Based on this finding, Isola et al. (2014) argued that stimulus memorability may not be consciously accessible to individual observers.

Limited individual awareness of stimulus memorability appears at odds with related lines of research demonstrating that individuals can competently assess their memory encoding success. More precisely, self-referential judgments of learning (JOL) made at the time of memory encoding reliably differentiate between subsequently remembered and forgotten stimuli (Fleming & Dolan, 2012; Koriat, 1997; Nelson & Dunlosky, 1991; Rhodes, 2016; Schwartz & Metcalfe, 2017). One plausible explanation for this discrepancy between JOLs and PMEs is the manner in which individuals access the memorability of a given stimulus. In contrast to Isola et al. (2014), where participants reported PMEs in the absence of explicit encoding demands, JOLs are made as participants attempt to encode stimuli in anticipation of later testing. This leaves open the possibility that stimulus memorability can only be accessed when individuals engage in intentional memory encoding.

However, stimulus memorability is not the only variable that participants have available when forming JOLs. JOLs can also be based on metacognitive assessments that are made about the quality of individual-specific encoding processes for a given stimulus. For example, not only is it the case that attentional fluctuations at encoding predict memory encoding success (deBettencourt et al., 2017; deBettencourt et al., 2020), but individuals have some awareness of these fluctuations (Adam & Vogel, 2017; McVay et al., 2009; J. Smallwood et al., 2004; J. M. Smallwood et al., 2003). Therefore, the predictive relationship between JOLs and subsequent memory performance may be exclusively dependent on these dynamic, individual-specific encoding variables and not on more stable properties of the stimuli themselves. If so, even when JOLs made by a given individual are predictive of subsequent memory performance, JOLs may be inconsistent across individuals and unable to predict inter-individual consistency in memory performance that results from stimulus memorability.

Here, we conducted a series of experiments to test whether individuals have conscious access to stimulus memorability and whether this potential access depends on encoding demands. Young adults reported JOLs while encoding images of real-world objects (Experiment 1A) or human faces (Experiment 1B) in anticipation of a later recognition memory test. If participants can consciously access stimulus memorability when forming JOLs, then JOLs for a given stimulus should be consistent across participants and able to predict interindividual consistency in recognition memory performance (i.e., stimulus memorability). To preview the results, we found that JOLs were indeed consistent across participants and predictive of stimulus memorability. Critically, however, this access to stimulus memorability during JOLs was not comprehensive. We found interindividual consistency in instances of unanticipated remembering and forgetting, when JOLs underestimated and overestimated stimulus memorability, respectively.

To test whether this partial access to stimulus memorability was dependent on encoding demands, we conducted Experiments 2A–B, in which participants reported PMEs of stimuli without any explicit demands for memory encoding. Here again, PMEs were consistent across participants and predictive of stimulus memorability. When we compared the access to memorability between JOLs and PMEs, we found that individuals accessed the same properties during both types of judgments, but individuals accessed additional properties during JOLs that were not accessed during PMEs. Taken together, these findings demonstrate that individuals have partial access to stimulus memorability and that this access is greater when individuals explicitly encode stimuli into memory.

## Experiment 1

### Method

#### Participants

For each experiment, we recruited 120 young adults through Prolific who resided in the USA or Canada at the time of the experiment (Experiment 1A: 18–31 years old,  $M_{\text{age}} = 24.19$  years,  $SD = 3.97$ ,  $n_{\text{female}} = 61$ ; Experiment 1B: 18–30 years old,  $M_{\text{age}} = 24.66$  years,  $SD = 3.69$ ,  $n_{\text{female}} = 53$ ). This sample size was determined to have each of 600 stimuli rated by 30 participants (see *Stimuli* and *Procedure* for details). Each participant provided electronic informed consent in accordance with the protocol approved by the Research Ethics Boards of the University of Toronto and received monetary compensation for their participation (7.50 £/hour). All participants reported fluency in English, normal or corrected-to-normal vision, no color blindness, no history of head injury, no history of mental

illness/condition, and no cognitive impairment/dementia. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (i.e., approval rate >90%).

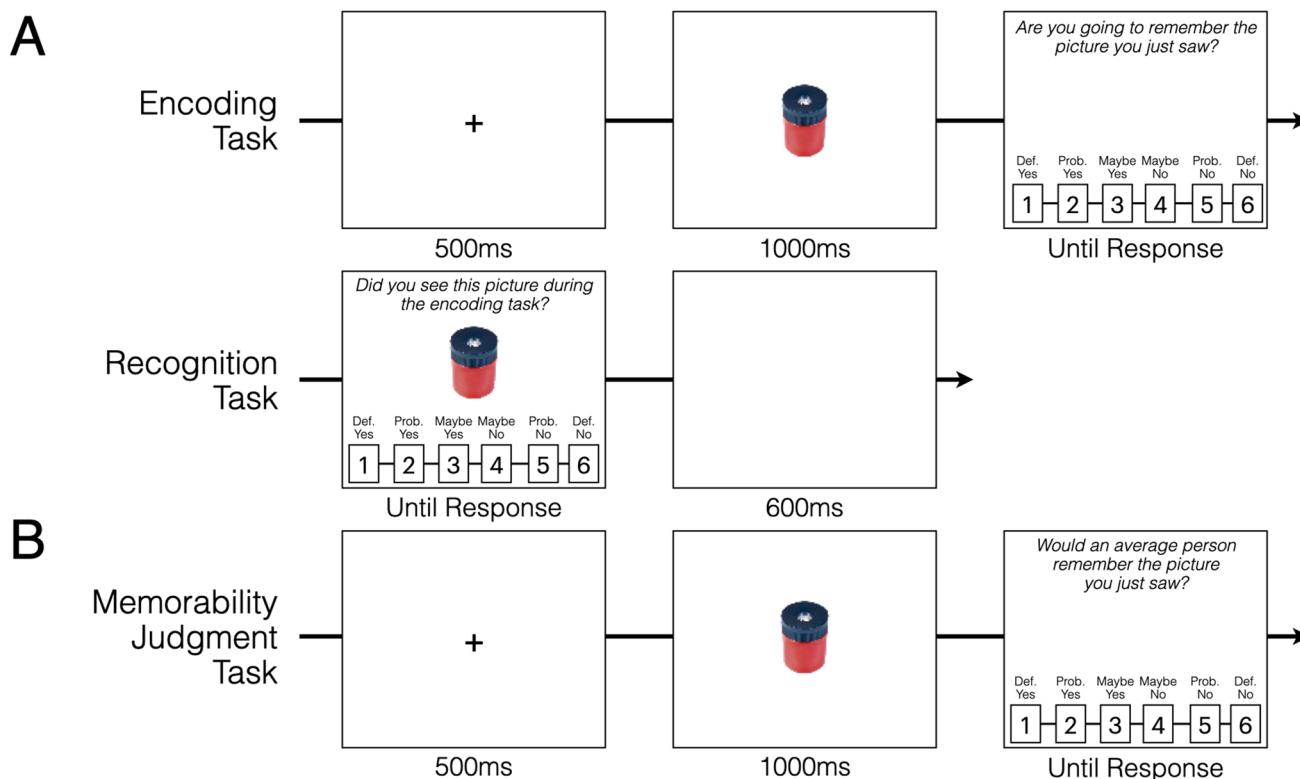
**Stimuli**

For Experiment 1A, we selected a set of 600 images of real-world objects from an existing database (Brady et al., 2008). This set was split into four sets of 150 images. For Experiment 1B, we selected a set of 600 face images from a different database (Bainbridge et al., 2013). This set was also split into four sets of 150 images. Each stimulus set was counterbalanced across participants in each experiment such that each image was studied or presented as a novel foil to an identical number (= 30) of participants.

**Procedure**

In Experiments 1A–B, participants performed an encoding task followed by an item recognition task (see Fig. 1a).

**Encoding task** Every trial began with the presentation of a fixation cross at the center of the screen for 500 ms. The fixation cross was then replaced by a to-be-remembered image at the center of the screen for 1,000 ms (Experiment 1A: real-world object; Experiment 1B: human face). Since we could not control the size or resolution of the computer monitors that participants used in our online experimental procedure, the to-be-remembered stimulus was fit to a square whose size was fixed proportionately to the vertical axis of the monitor (12% and 20% for Experiments 1A and 1B, respectively). Five hundred milliseconds after the offset of the to-be-remembered image, a question and 6-point Likert scale were presented simultaneously. The question read: “Are you going to remember the picture you just saw?” Participants then completed a JOL by indicating how likely they were to remember the just-seen stimulus during a subsequent recognition task by clicking on one of the following buttons: 1 = *Definitely yes*, 2 = *Probably yes*, 3 = *Maybe yes*, 4 = *Maybe no*, 5 = *Probably no*, 6 = *Definitely no*. The Likert scale remained on the screen until a response was provided. Each participant completed 150 trials to encode 150 different memory stimuli. The presentation order of the stimuli was randomized across participants.



**Fig. 1** Experimental schematics. **a** Experiment 1A schematic. The top row shows the trial procedure for the Encoding Task, and the bottom row shows the trial procedure for the Recognition Task. **b** Experiment

2A schematic. Experiments 1B and 2B used identical procedures to 1A and 2A, respectively, with images of human faces in place of real-world objects

**Recognition task** In every trial, participants were presented a test stimulus at the center of the screen. A question was presented above the stimulus that read: “Did you see this picture during the encoding task?” with a corresponding 6-point Likert scale presented below the stimulus. The size of the test stimulus was identical to the memory stimulus in the Encoding Task. Participants completed a recognition judgment on the test stimulus by clicking one of the following buttons: 1 = *Definitely yes*, 2 = *Probably yes*, 3 = *Maybe yes*, 4 = *Maybe no*, 5 = *Probably no*, 6 = *Definitely no*. After each recognition judgment, the screen turned blank for a 600-ms intertrial interval. Participants saw 150 old images and 150 new images in a pseudorandom order.

## Analyses

### Memorability scores

To assess participants’ access to stimulus memorability, we tested whether JOLs were consistent across observers and predictive of consistency in recognition responses. However, stimulus memorability is not the only stimulus property that can produce consistent JOLs and recognition responses. For example, the typicality of an image can produce feelings of familiarity that are independent of encoding (e.g., Bartlett et al., 1984; Light et al., 1979). Therefore, when groups of individuals successfully recognize the same image as being old, these recognition responses can be driven by properties that determined the ease of initial encoding across individuals (i.e., stimulus memorability) or by how typical the image appeared to the individuals during recognition (i.e., general stimulus familiarity). As such, it is difficult, if not impossible, to disentangle the effect of general stimulus familiarity from stimulus memorability within responses that are made to studied images. Critically, however, recognition responses that are made to unstudied foils can be influenced by general stimulus familiarity, but not by stimulus memorability, since there was no initial encoding of the foils that took place. Thus, to remove the effect of general stimulus familiarity from recognition responses and isolate the effect of stimulus memorability, we computed *memorability scores* by subtracting recognition responses that were made when the image was new (= general familiarity) from recognition responses that were made when the image was old (= stimulus memorability + general familiarity). This procedure is analogous to calculating corrected hit rates that account for the role of guessing in recognition memory paradigms.

### Split-half correlation analysis for interindividual consistency

To test the interindividual consistency in our measures of interest (e.g., recognition response, JOL), we performed a

conventional split-half analysis. First, we randomly split participants into two groups and computed the average response of interest for each stimulus in each group. Then, we computed the correlation for the average response of interest between the two groups. We repeated this process 1000 times to estimate the distribution of split-half correlation coefficients. To establish the null distribution, we repeated the same procedure, but in each iteration, we shuffled the stimulus labels in one of the groups.

### Residual regression analysis

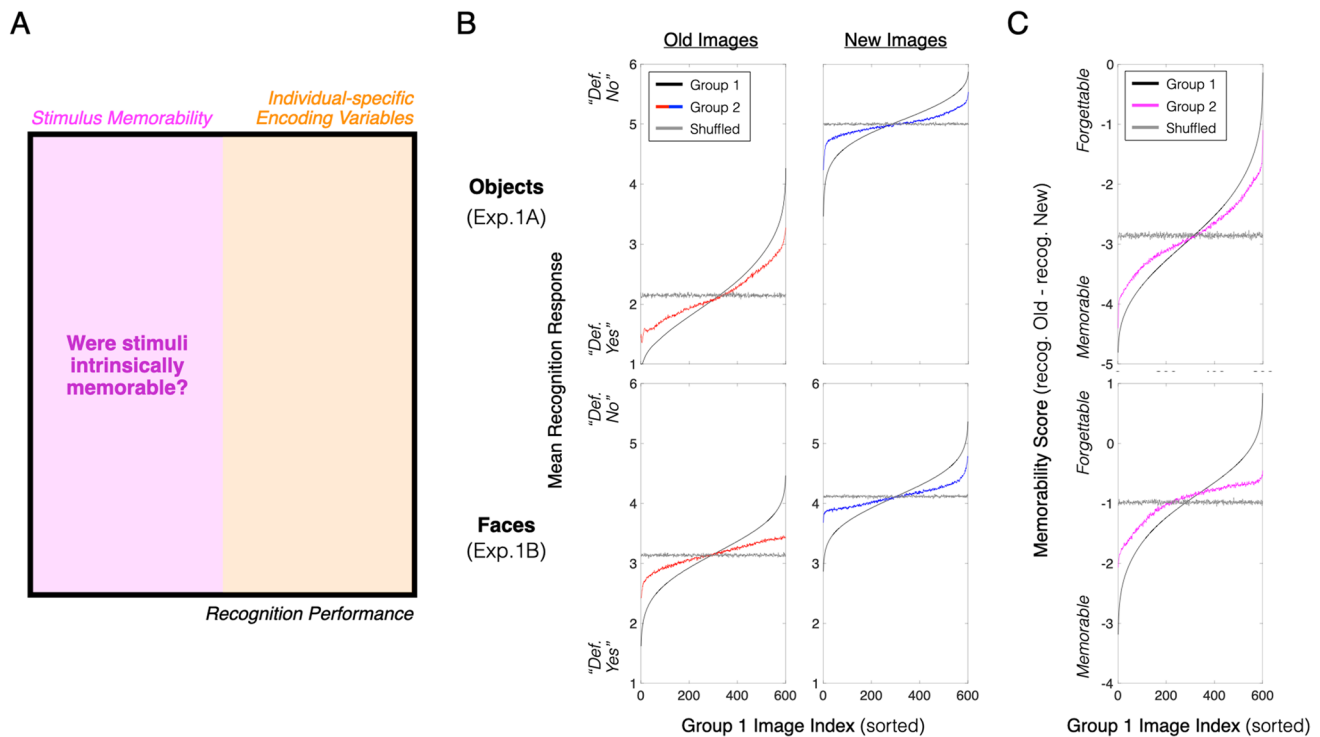
To test whether participants relied on both stimulus memorability and individual-specific encoding variables (e.g., fluctuating cognitive states) when forming JOLs, and whether these distinct factors influenced recognition performance, we employed residual regression analyses based on the following logic:

- (1) Assume Information A (e.g., stimulus memorability) and B (e.g., individual-specific cognitive state) both contribute to Performance C (e.g., memory encoding)
- (2) Assume individuals use Information A and B to form predictions about Performance C (= C', e.g., JOL)
- (3) If (1) and (2) are true, the residual C' after regressing out A should still predict Performance C because individuals are aware of the contribution of B to C.
- (4) On the other hand, if B does not contribute uniquely to C', then the residual C' after regressing out A should no longer predict C.

## Results

### Validating stimulus memorability

We first aimed to validate the existence of stimulus memorability in our stimulus set (Fig. 2a). Split-half correlation analyses revealed that recognition responses were consistent across participants when the stimuli were old images (Fig. 2b); Experiment 1A: mean  $r = .62$ ,  $t(1998) = 3.46 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 15.44$ ; Experiment 1B: mean  $r = .41$ ,  $t(1998) = 2.19 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 9.81$ , as well as new images (Fig. 2b); Experiment 1A: mean  $r = .44$ ,  $t(1998) = 1.64 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 7.38$ ; Experiment 1B: mean  $r = .40$ ,  $t(1998) = 1.48 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 6.63$ . The observed consistency in recognition responses to unstudied images demonstrated a need to disentangle the effect of general stimulus familiarity from stimulus memorability in participants’ recognition responses (see *Analyses*). To do this, we calculated memorability scores that isolated the effect of stimulus memorability in participants’ recognition responses and subjected these corrected measures to split-half analysis. In doing so, we found that memorability



**Fig. 2** Stimulus memorability in Experiments 1A-B. **a** Schematic depiction of the research question addressed by the accompanying figures. **b** Interindividual consistency in recognition responses in Experiments 1A (*top*) and 1B (*bottom*) when images were old (*left*) and new (*right*). **c** Interindividual consistency in corrected recognition responses (i.e., memorability scores) in Experiments 1A (*top*)

and 1B (*bottom*). Black lines show the mean recognition responses for Group 1 from the lowest to highest scoring images. Red, blue, and magenta lines show the mean recognition responses for corresponding images in Group 2. The gray lines show the mean recognition responses for corresponding images in Group 2 when image indices were shuffled (i.e., null distribution). (Color figure online)

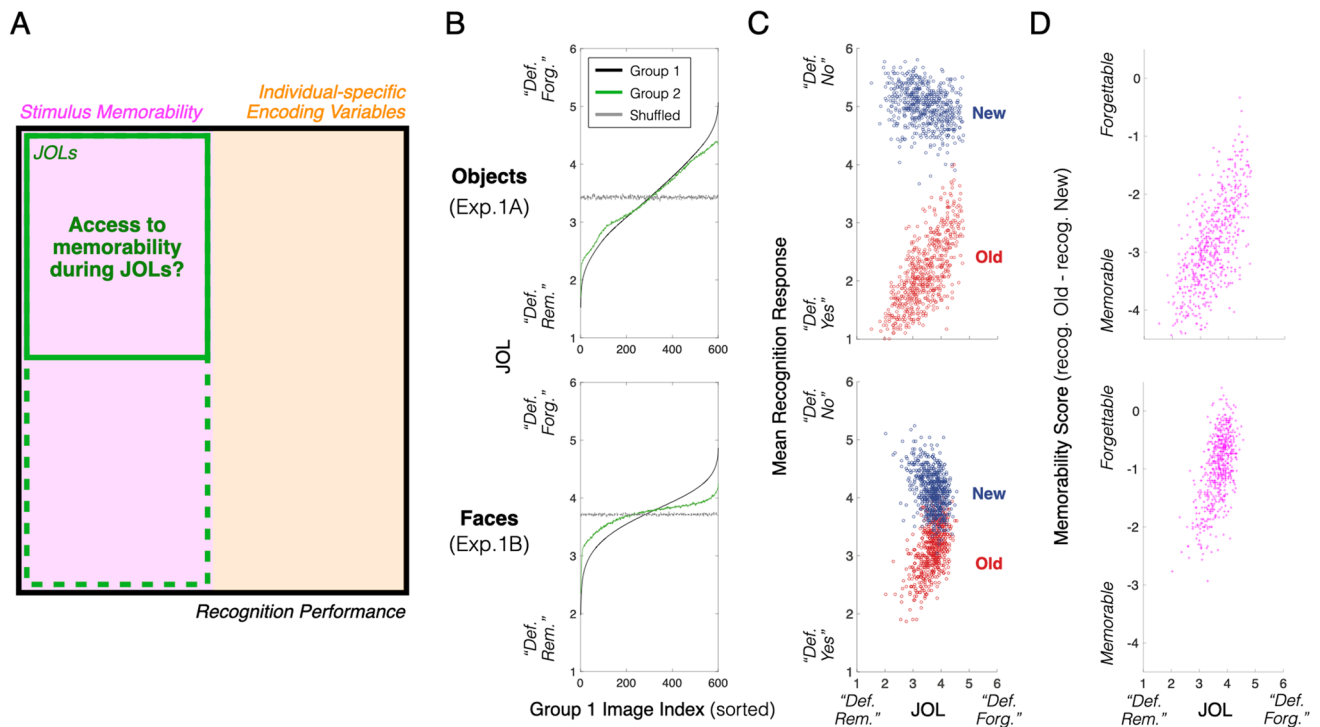
scores were consistent across participants (Fig. 2c); Experiment 1A: mean  $r = .65$ ,  $t(1998) = 3.58 \times 10^2$ ,  $p < .001$ , Cohen's  $d = 16.01$ ; Experiment 1B: mean  $r = .46$ ,  $t(1998) = 2.17 \times 10^2$ ,  $p < .001$ , Cohen's  $d = 9.85$ ; see Supplementary Information for  $t(1998) = 2.17 \times 10^2$ ,  $p < .001$ , Cohen's  $d = 9.85$ ; see Supplementary Information for corroborating results in individual-differences and permutation-based analyses. These findings confirm that some images in our stimulus set were more intrinsically memorable than others.

#### Access to stimulus memorability during JOLs is reliable, but imperfect

If participants were consciously aware of an image's memorability while forming JOLs, then we should find that JOLs for a given stimulus were consistent across participants (i.e., JOL-ability; Fig. 3a). By the same account, the average JOL for a given stimulus should predict its average memorability score. As can be seen in Fig. 3b, average JOLs for a random half of our participants predicted the average JOLs for the remaining half, confirming access to a common set of stimulus properties during JOL formation, Experiment 1A: mean  $r = .81$ ,  $t(1998) = 5.10 \times 10^2$ ,  $p < .001$ , Cohen's  $d =$

22.82; Experiment 1B: mean  $r = .46$ ,  $t(1998) = 1.51 \times 10^2$ ,  $p < .001$ , Cohen's  $d = 6.74$ . This JOL-ability was found to predict average recognition responses that were made when the stimulus was an old image (Fig. 3c); Experiment 1A:  $r(598) = .71$ ,  $R^2 = .50$ ,  $p < .001$ ; Experiment 1B:  $r(598) = 0.51$ ,  $R^2 = .26$ ,  $p < .001$ , and when it was a new image (Fig. 3c);  $r(598) = -.32$ ,  $R^2 = .10$ ,  $p < 0.001$ ; Experiment 1B:  $r(598) = -.38$ ,  $R^2 = .14$ ,  $p < .001$ . More importantly, memorability scores were reliably predicted by JOL-ability (Fig. 3d); Experiment 1A:  $r(598) = .68$ ,  $R^2 = .46$ ,  $p < .001$ ; Experiment 1B:  $r(598) = .60$ ,  $R^2 = .36$ ,  $p < .001$  (see Supplementary Information for corroborating results in individual-differences and permutation-based analyses), suggesting that participants were aware of stimulus memorability during JOL formation and used those properties to predict subsequent recognition performance.

We then sought to determine the extent of participants' conscious access to stimulus memorability (Fig. 4a). If access was comprehensive, then participants' JOLs should fully capture the variability in memorability between stimuli. In other words, any deviations in an individual's recognition response from their respective JOL should reflect an idiosyncratic fluctuation in cognitive state or stimulus



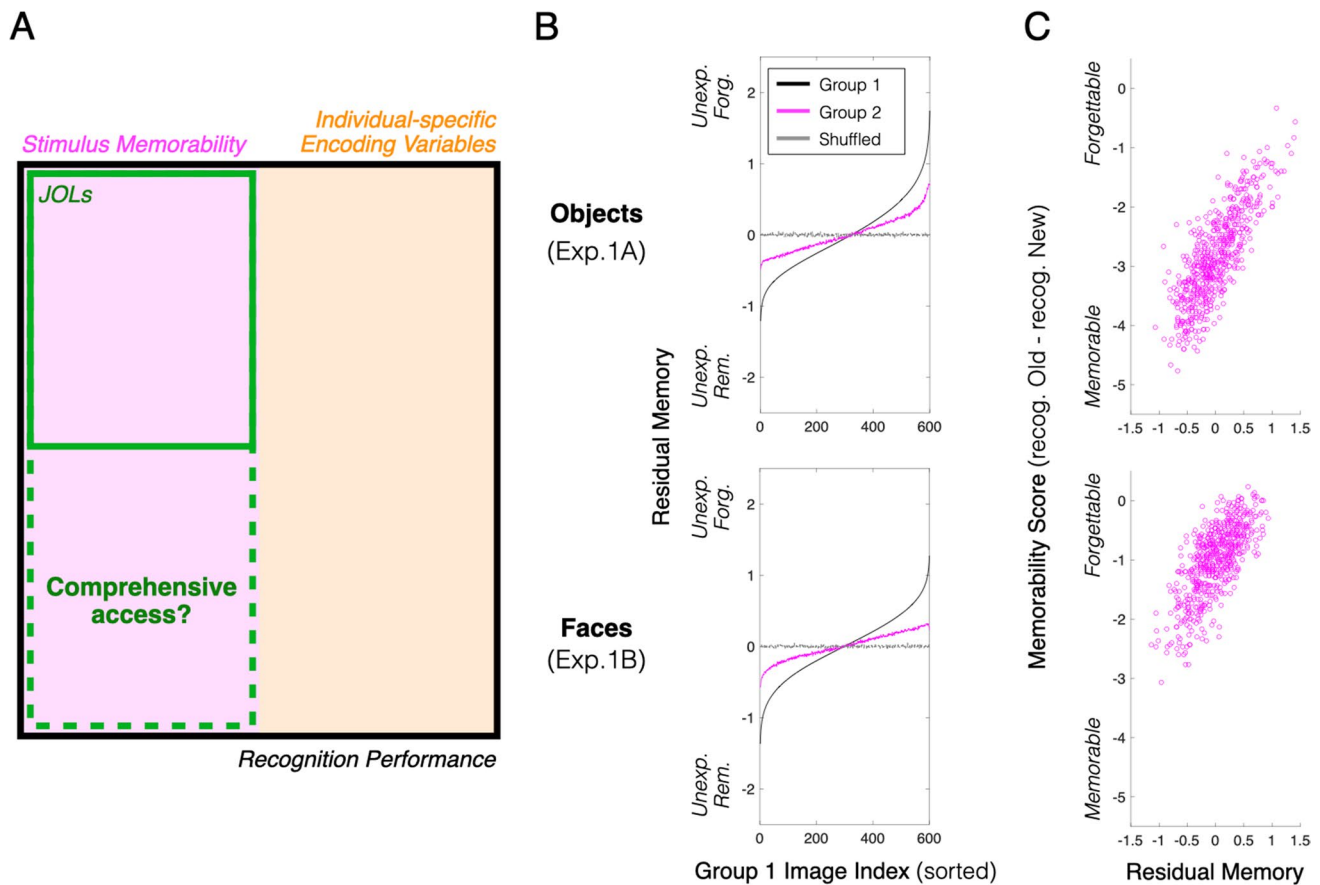
**Fig. 3** Individuals incorporate stimulus memorability into JOLs. **a** Schematic depiction of the research question addressed by the accompanying figures. JOLs = judgments of learning. **b** Interindividual consistency in JOLs in Experiments 1A (top) and 1B (bottom). Black lines show the mean JOLs for Group 1, with images sorted from the lowest to highest mean response. Green lines show the mean JOLs for corresponding images in Group 2. The gray lines show the mean

JOLs for corresponding images in Group 2 when image indices were shuffled (i.e., null distribution). **c** Scatterplots illustrating the relationship between average JOLs (i.e., JOL-ability) and average recognition responses when images were old and new. **d** Scatterplots illustrating the relationship between average JOLs (i.e., JOL-ability) and average corrected recognition responses (i.e., memorability score). (Color figure online)

processing at the time of encoding that was not consistent across individuals. To test this possibility, for each participant, we regressed JOLs out of recognition responses for old images and then computed the residual memory score for each stimulus. When we subjected these residual memory scores to split-half analyses, we found that they were reliably consistent across individuals (Fig. 4b); Experiment 1A: mean  $r = .49$ ,  $t(1998) = 3.30 \times 10^2$ ,  $p < 0.001$ , Cohen's  $d = 14.76$ ; Experiment 1B: mean  $r = .35$ ,  $t(1998) = 2.31 \times 10^2$ ,  $p < .001$ , Cohen's  $d = 10.34$  (see Supplementary Information for corroborating results in individual-differences and permutation-based analyses), meaning that participants unexpectedly remembered and forgot consistent sets of stimuli. We then correlated residual memory scores with memorability scores to see if the observed consistency in residual memory was attributable to properties of memorability that were not incorporated into JOLs. We found that residual memory scores did indeed predict memorability scores (Fig. 4c); Experiment 1A:  $r(598) = .81$ ,  $R^2 = .65$ ,  $p < .001$ ; Experiment 1B:  $r(598) = 0.72$ ,  $R^2 = .52$ ,  $p < .001$ , demonstrating that participants' access to stimulus memorability was not perfect and that some of these properties went undetected.

### JOLs incorporate stimulus memorability and idiosyncratic fluctuations in encoding success

In our split-half correlational analyses, we found that interindividual consistency in JOLs predicted interindividual consistency in recognition performance, demonstrating conscious access to stimulus memorability. From here, we conducted an individual differences analysis to investigate whether participants also incorporated individual-specific encoding variables, such as their current cognitive state, into JOLs (Fig. 5a). To do this, we removed the effect of stimulus memorability and general stimulus familiarity from individuals' JOLs and recognition responses and tested whether they were still predictive of one another. Specifically, we computed residual JOLs by regressing out JOL-ability and computed residual recognition responses to old images by regressing out the interindividual consistency in responses to old images. When we correlated residual JOLs with residual recognition performance, we found that there was indeed a predictive relationship between these idiosyncratic measures (Fig. 5b); Experiment 1A: mean  $r = .17$ ,  $t(119) = 1.34 \times 10$ ,  $p < .001$ , Cohen's  $d = 1.23$ ; Experiment 1B: mean  $r = .14$ ,  $t(119) = 1.52 \times 10$ ,  $p < .001$ , Cohen's  $d = 1.39$ ;



**Fig. 4** Access to stimulus memorability during JOLs is not comprehensive. **a** Schematic depiction of the research question addressed by the accompanying figures. JOLs = judgments of learning. **b** Inter-individual consistency in average residual recognition responses after regressing out individual JOLs (i.e., residual memory scores) in Experiments 1A (top) and 1B (bottom). Black lines show the mean residual recognition responses for Group 1, with images sorted from

the lowest to highest mean response. Magenta lines show the mean residual recognition responses for corresponding images in Group 2. The gray lines show the mean residual recognition responses for corresponding images in Group 2 when image indices were shuffled (i.e., null distribution). **c** Scatterplots illustrating the relationship between residual memory scores and average corrected recognition responses (i.e., memorability scores). (Color figure online)

see Supplementary Information for corroborating results in permutation-based analyses. Thus, JOLs were multi-faceted, incorporating intrinsic stimulus memorability and individual-specific encoding variables, such as fluctuating cognitive states and stimulus processing.

## Experiment 2

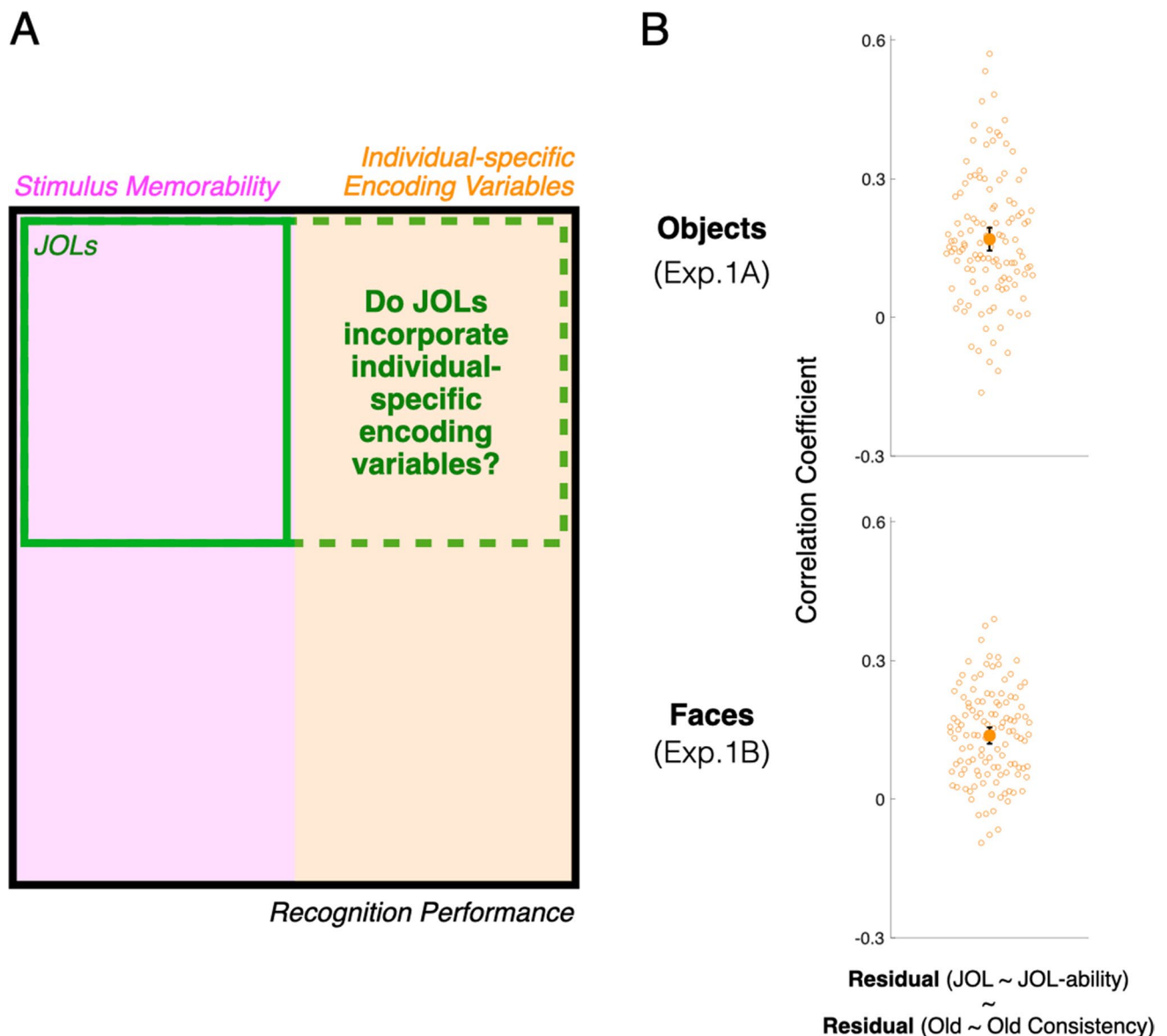
The results of Experiment 1 suggest that individuals are aware of stimulus memorability when encoding visual information into memory. However, it is unclear whether explicit encoding is required to access stimulus memorability. If so, PME made in the absence of attempted encoding should not predict stimulus memorability even if PMEs are consistent across individuals. Conversely, if individuals can access stimulus memorability regardless of encoding, PMEs should be consistent

across individuals (i.e., PME-ability) and predictive of stimulus memorability. In fact, PME-ability should be even more consistent than JOL-ability, since individuals do not need to incorporate individual-specific encoding variables that can conflict with stimulus-intrinsic properties. To test this question in Experiment 2, we removed all encoding demands and asked participants to report how likely an average person would be to remember a given stimulus.

## Method

### Participants

For each experiment, we recruited 120 young adults through Prolific who resided in the U.S. or Canada at the time of the experiment (Experiment 2A: 18–30 years old,  $M_{\text{age}} = 22.68$  years,  $SD = 3.13$ ,  $n_{\text{female}} = 91$ ; Experiment



**Fig. 5** Individuals Incorporate idiosyncratic variables into JOLs. **a** Schematic depiction of the research question addressed by the accompanying figures. JOLs = judgments of learning. **(b)** Correlations between the residuals in individual JOLs after regressing out average JOLs across participants (i.e., JOL-ability) and the residuals in

individual recognition responses for old pictures after regressing out average recognition responses to old pictures (i.e., old consistency) in Experiment 1A (*top*) and Experiment 1B (*bottom*). Filled colored dots with short black error bars show the mean correlation coefficient with the standard error of the mean. (Color figure online)

2B: 18–33 years old,  $M_{\text{age}} = 22.90$  years,  $SD = 3.57$ ,  $n_{\text{female}} = 90$ ). This sample size was determined to have each of 600 stimuli rated by 30 participants. Each participant provided electronic informed consent in accordance with the protocol approved by the Research Ethics Boards of the University of Toronto and received monetary compensation for their participation (7.50 £/hour). All participants were screened using the same criteria as Experiment 1.

#### Stimuli

The stimulus sets were identical to those used in Experiment 1.

#### Procedure

In Experiments 2A–B, participants performed the memorability judgment task (see Fig. 1b).



**Memorability judgment task** This task was identical to the Encoding task used in Experiment 1 with the following exceptions. Instead of providing a JOL for each presented stimulus, participants reported the perceived memorability of the stimulus by answering the following question: “Would an average person remember the picture you just saw?” Participants were not provided any instruction to remember the stimuli, and there was no recognition test that followed.

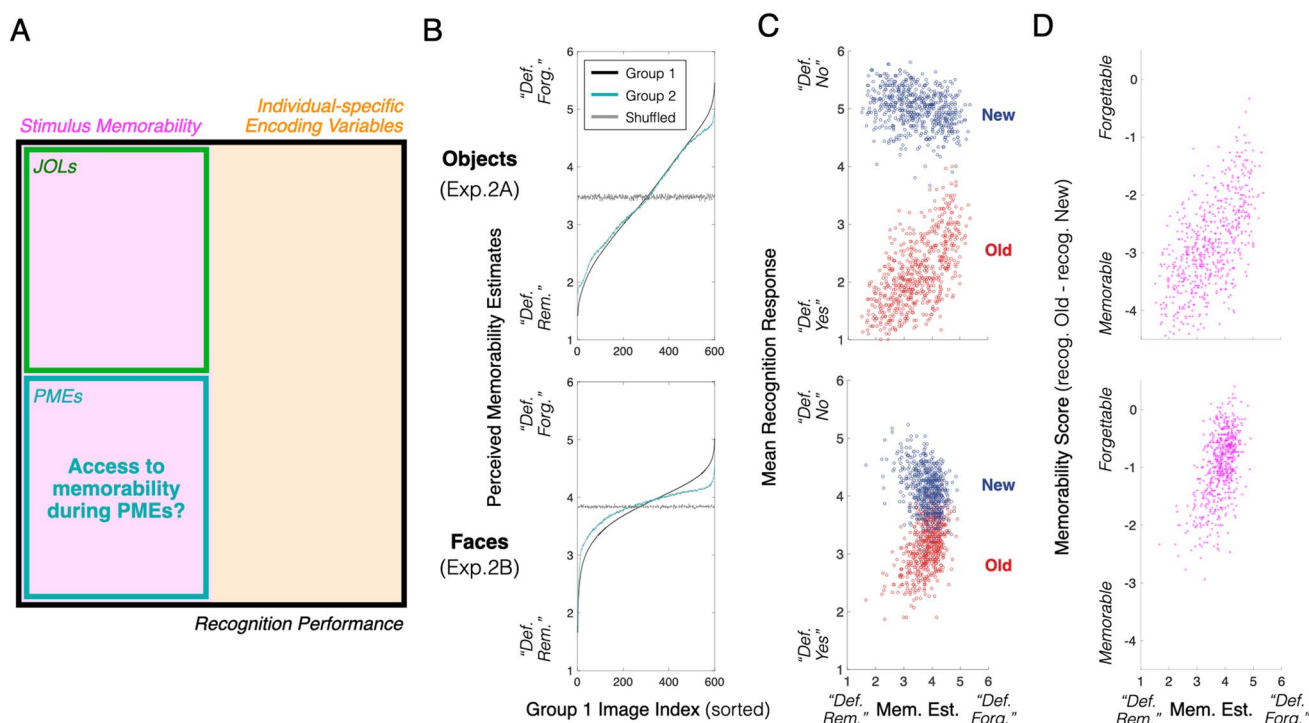
**Results**

**Accessing stimulus memorability does not require encoding, but encoding increases access**

To test whether access to memorability was dependent on encoding demands, we measured interindividual consistency in PME-s and assessed whether PME-s predicted memorability (Fig. 6a). As can be seen in Fig. 6b, our split-half analyses found reliable interindividual consistency in PME-s, Experiment 2A: mean  $r = .88$ ,  $t(1998) = 6.02 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 26.93$ ; Experiment 2B: mean  $r = .66$ ,  $t(1998) = 3.59 \times 10^2$ ,  $p < .001$ , Cohen’s  $d = 16.04$ . These consistent PME-s successfully

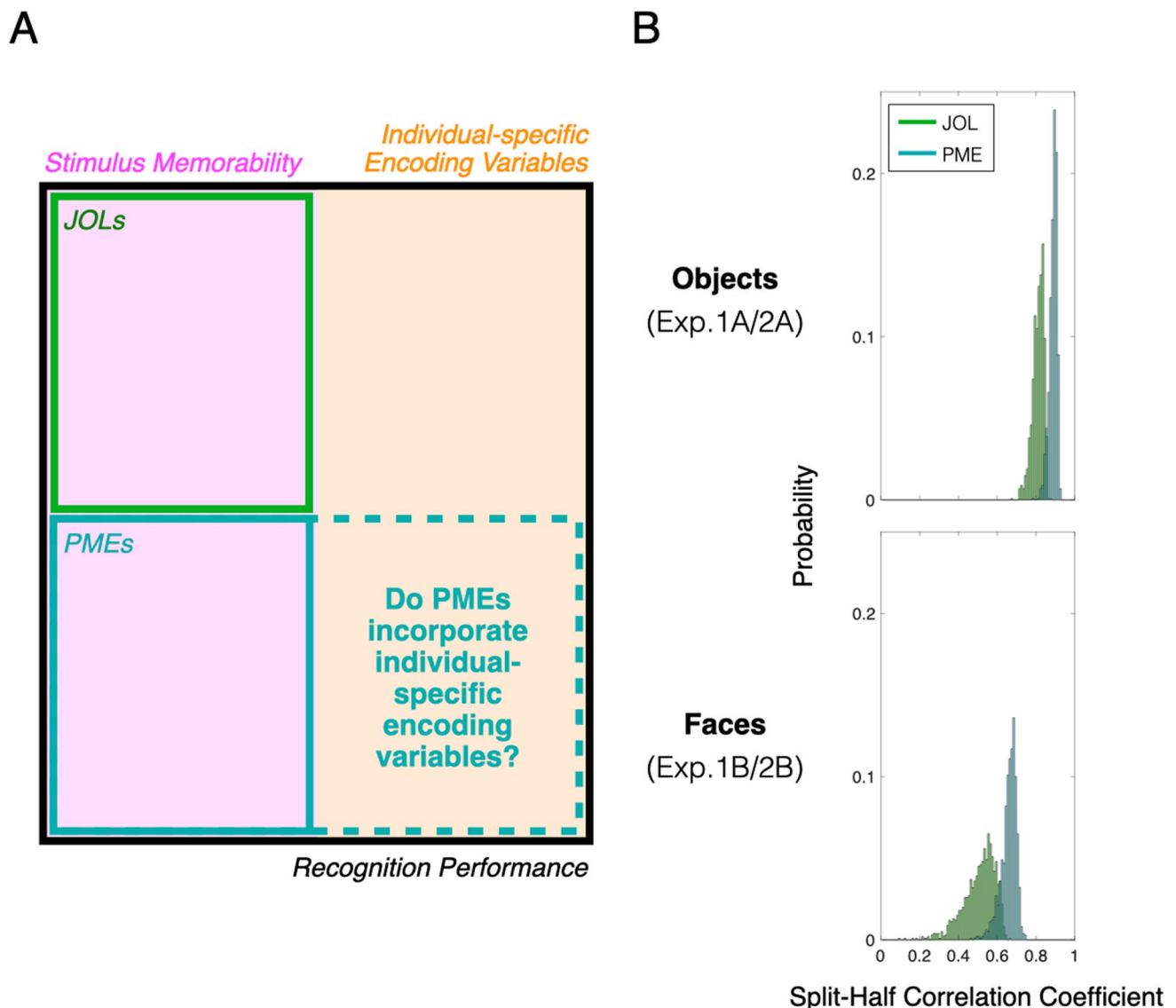
predicted the recognition responses made in Experiment 1 when the stimuli were old images (Fig. 6c); Experiment 2A:  $r(598) = .62$ ,  $R^2 = .38$ ,  $p < .001$ ; Experiment 2B:  $r(598) = .48$ ,  $R^2 = .23$ ,  $p < .001$ , and when they were new images (Fig. 6c); Experiment 2A:  $r(598) = -.29$ ,  $R^2 = .08$ ,  $p < .001$ ; Experiment 2B:  $r(598) = -.34$ ,  $R^2 = 0.12$ ,  $p < .001$ . More importantly, PME-s predicted memorability scores observed in Experiment 1 (Fig. 6d); Experiment 2A:  $r(598) = .60$ ,  $R^2 = .36$ ,  $p < .001$ ; Experiment 2B:  $r(598) = 0.55$ ,  $R^2 = .30$ ,  $p < .001$ . These findings appear to suggest that individuals had access to stimulus memorability without needing to encode stimuli.

However, it is possible that participants continued to encode stimuli as a strategy to complete PME-s, by extrapolating their own encoding success to that of the average observer. If so, participants’ PME-s should be influenced by individual-specific encoding variables just like JOL-s (Fig. 7a). To test this, we compared PME-ability with JOL-ability. If participants did not encode stimuli when computing PME-s, then PME-s should be more consistent across individuals than JOL-s. As depicted in Fig. 7b, the average split-half correlation was higher for PME-s than JOL-s, Experiment 2A:  $t(1998) = 6.57 \times 10$ ,  $p < .001$ , Cohen’s  $d = 2.94$ ; Experiment 2B:  $t(1998) = 6.59 \times 10$ ,  $p < .001$ .



**Fig. 6** Consistent and predictive estimates of stimulus memorability without encoding. **a** Schematic depiction of the research question addressed by the accompanying figures. JOL-s = judgments of learning; PME-s = perceived memorability estimates. **b** Interindividual consistency in PME-s in Experiments 2A (top) and 2B (bottom). Black lines show the mean memorability estimates for Group 1 with images sorted from the lowest to highest mean response. Teal lines show the mean memorability estimates for corresponding images in Group

2. The gray lines show the mean memorability estimates for corresponding images in Group 2 when image indices were shuffled (i.e., null distribution). **c** Scatterplots illustrating the relationship between average memorability estimates (i.e., PME-ability) and average recognition responses when images were old and new. **d** Scatterplots illustrating the relationship between average memorability estimates (i.e., PME-ability) and average corrected recognition responses (i.e., memorability scores). (Color figure online)



**Fig. 7** Higher prediction consistency in the absence of encoding. **a** Schematic depiction of the research question addressed by the accompanying figures. JOLs = judgments of learning; PMEs = Perceived

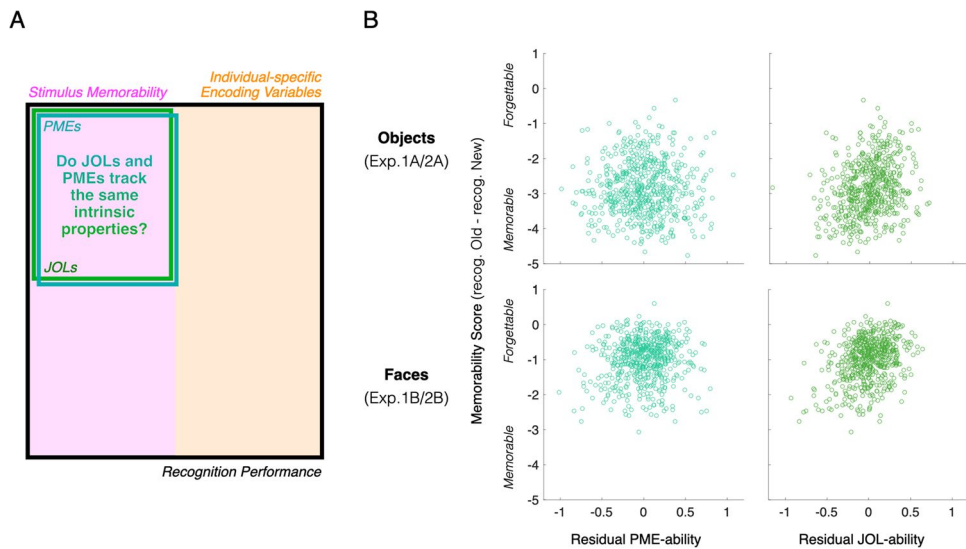
memorability estimates. **b** Distributions of 10,000 split-half correlation coefficients for JOLs in Experiment 1 and PMEs in Experiment 2. (Color figure online)

.001, Cohen's  $d = 2.95$ , confirming that the removal of encoding demands eliminated the incorporation of individual-specific encoding variables by participants. Given that encoding does not appear to be necessary for accessing memorability, we tested whether participants accessed the same properties of memorability during JOLs and PMEs. We regressed JOL-ability out of PME-ability (and vice versa) for every image and measured whether residual PME-ability still predicted memorability. We found that PMEs no longer predicted memorability after accounting for JOLs (Fig. 8b); Experiment 2A:  $r(598) < .01$ ,  $R^2 < .01$ ,  $p = .954$ ; Experiment 2B:  $r(598) = .09$ ,  $R^2 < .01$ ,  $p = .009$ , but JOLs continued to predict memorability after accounting for PMEs (Fig. 8b); Experiment 2A:  $r(598) = 0.27$ ,  $R^2 = .07$ ,  $p$

$< .001$ ; Experiment 2B:  $r(598) = .33$ ,  $R^2 = .11$ ,  $p < .001$ . These findings suggest that individuals accessed a common set of memorability properties regardless of encoding, but that there were additional properties that were only accessed when individuals encoded stimuli into memory.

**Discussion**

Are individuals aware of how memorable a given stimulus is? Across two experiments, we demonstrated that individuals have conscious access to stimulus memorability when computing JOLs during memory encoding and when

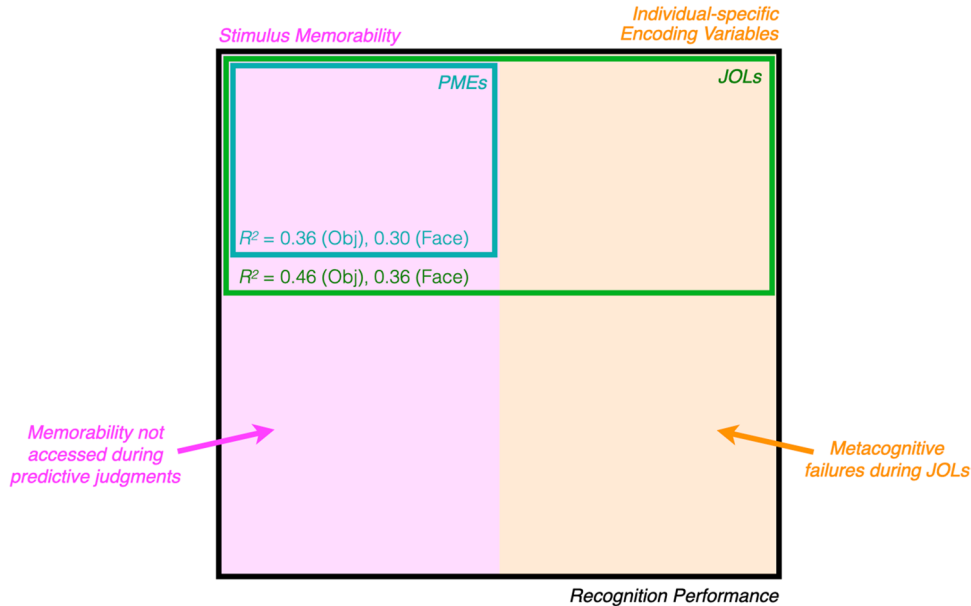


**Fig. 8** Asymmetric access to stimulus memorability during JOLs and PMEs. **a** Schematic depiction of the research question addressed by the accompanying figures. JOLs = judgments of learning; PMEs = perceived memorability estimates. **b** Scatterplots illustrating the relationship between average corrected recognition responses (i.e., mem-

orability scores) and residual PME-ability or residual JOL-ability, respectively. Each residual measure (e.g., residual PME-ability) was computed by regressing interindividual consistency in one judgment (e.g., JOL-ability) out of the interindividual consistency in the other respective judgment (e.g., PME-ability). (Color figure online)

computing PMEs in the absence of encoding demands. However, we also found that encoding grants individuals additional access to stimulus memorability (see Fig. 9 for a summary of the mapping between predictive judgments and memory performance).

The predictive relationship between subjective memorability judgments and stimulus memorability appears to directly contradict previous work showing that PMEs do not predict subsequent memory performance (Isola et al., 2014). One possible explanation for this discrepancy is the



**Fig. 9** Mapping between predictive judgments of remembering and veridical memory performance. Recognition memory performance reflects the composite influence of intrinsic stimulus properties that determine the ease of encoding across individuals (i.e., stimulus memorability) and cognitive states and encoding processes that fluctuate from moment to moment (i.e., individual-specific encoding variables). Individuals are able to access both of these sources of encoding variability and incorporate them into self-referential judgments of learning (JOL) that predict future recognition performance. However,

both sources are only partially accessed; individuals fail to detect consistent aspects of memorability and can experience metacognitive failures during encoding. When individuals form perceived memorability estimates (PME) about stimuli in the absence of explicit encoding, access to memorability is preserved but more constrained than the access achieved during JOLs. Thus, encoding is not necessary for individuals to access stimulus memorability and predict recognition performance, but it does increase the amount of access that is available. (Color figure online)

inconsistency in stimuli that were used in each study. In the present study, stimuli were composed of single objects or faces that were superimposed on a white background.

These minimal stimulus configurations encouraged participants to focus on a single, consistent item when evaluating stimulus memorability. However, in Isola et al. (2014), participants evaluated stimuli that were composed of multiple objects embedded in naturalistic backgrounds. This increased stimulus complexity may have resulted in different participants focusing on different aspects of a given stimulus, including aspects that were not predictive of stimulus memorability. There are also naturally occurring differences in the dimensionality of scene images compared to object images (e.g., Torralba & Oliva, 2003) that may have challenged observers' ability to estimate stimulus memorability. Such hypotheses are consistent with our observation that individuals lack comprehensive access to stimulus memorability and may not be able to guide their conscious processing of stimuli based purely on these intrinsic properties.

Future work should also determine whether the consciously accessible properties of stimulus memorability are also consciously explicable by observers. One of the tantalizing difficulties in stimulus memorability research has been parsing memorability into its elementary components (Bainbridge et al., 2013; Bainbridge et al., 2017; Lin et al., 2021; Xie et al., 2020). To this end, computational approaches have demonstrated some success in predicting memorability (e.g., Basavaraju et al., 2018; Celikkale et al., 2015; Lukavský & Děchtěrenko, 2017; Squalli-Houssaini et al., 2018). For example, in a study by Khosla et al. (2015), neural network predictions showed a 0.64 rank correlation with objective memory performance, which is approximate to the correlations achieved here by human predictions. Yet, neither humans nor computers have provided an exhaustive profile of the properties that define stimulus memorability. One interesting route towards closing this gap may be to simply ask observers to report the rationale behind their predictive judgments. Such qualitative data may help to uncover unidentified memorability components and narrow the pool of known components that observers might not have access to.

While beyond the scope of the present study, we speculate here about the stimulus properties that were not accessible to observers. One possibility is that observers estimate stimulus memorability based exclusively on semantic properties while leaving out non-semantic visual properties. Previous work has shown that a sizable proportion of memorability for faces (e.g., Bainbridge et al., 2013) and scenes (e.g., Isola et al., 2014) can be attributed to semantic properties that are commonly perceived. Critically, however, two images depicting comparable semantic properties can show different patterns of memorability (e.g., Bylinskii et al., 2015), implying a unique contribution by non-semantic properties.

Indeed, Lin et al. (2021) demonstrated that removing semantic information from images through phase scrambling did not eliminate stimulus memorability. Future work should address whether partial access to memorability can be explained by an exclusive reliance on semantic properties that sometimes belie variability in lower-level visual properties.

Finally, our results demonstrated that JOLs stemmed from two dissociable factors—namely, stimulus-intrinsic memorability and individual-specific encoding variables. These distinct variables map nicely onto a classic theory of JOLs, which posits that individuals integrate intrinsic and extrinsic factors when predicting future stimulus remembering (Koriat, 1997). Moreover, these dissociable cognitive variables may explain the overlapping, but dissociable, neural activities that separate JOL computations from objective memory encoding (Do Lam et al., 2012; Fleming & Dolan, 2012; Kao et al., 2005; Yang et al., 2015). Specifically, JOL computations rely on unique contributions by the dorsolateral and medial prefrontal cortex that are not observed during memory encoding alone. Future work should investigate whether stimulus-intrinsic memorability and individual-specific encoding variables provide fitting cognitive analogues for these dissociable neural processes.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.3758/s13423-022-02166-1>.

**Open practices statement** The data, stimuli, and experimental codes are posted publicly at the Open Science Framework (<https://osf.io/qrxs3/>).

**Funding** This research was supported by the Natural Sciences and Engineering Research Council (RGPIN-2017-06866) and the Connaught New Researcher Award.

## Declarations

**Conflicts of interest** The authors have no conflicts of interest to declare that are relevant to the content of this article.

## References

- Adam, K. C. S., & Vogel, E. K. (2017). Confident failures: Lapses of working memory reveal a metacognitive blind spot. *Attention, Perception, & Psychophysics*, *79*(5), 1506–1523.
- Bainbridge, W. A., Isola, P., & Oliva, A. (2013). The intrinsic memorability of face photographs. *Journal of Experimental Psychology: General*, *142*(4), 1323–1334.
- Bainbridge, W. A., Dilks, D. D., & Oliva, A. (2017). Memorability: A stimulus-driven perceptual neural signature distinctive from memory. *NeuroImage*, *149*, 141–152.
- Bartlett, J. C., Hurrey, S., & Thorley, W. (1984). Typicality and familiarity of faces. *Memory & Cognition*, *12*(3), 219–228.

- Basavaraju, S., Mittal, P., & Sur, A. (2018, October). Image memorability: The role of depth and motion. *2018 25th IEEE International Conference on Image Processing (ICIP)* (pp. 699–703). IEEE. <https://doi.org/10.1109/ICIP.2018.8451334>
- Bower, G. H., & Karlin, M. B. (1974). Depth of processing pictures of faces and recognition memory. *Journal of Experimental Psychology*, *103*(4), 751–757. <https://doi.org/10.1037/h0037190>
- Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2008). Visual long-term memory has a massive storage capacity for object details. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(38), 14325–14329.
- Brady, T. F., Konkle, T., Gill, J., Oliva, A., & Alvarez, G. A. (2013). Visual long-term memory has the same limit on fidelity as visual working memory. *Psychological Science*, *24*(6), 981–990.
- Broers, N., Potter, M. C., & Nieuwenstein, M. R. (2018). Enhanced recognition of memorable pictures in ultra-fast RSVP. *Psychonomic Bulletin & Review*, *25*(3), 1080–1086.
- Bylinskii, Z., Isola, P., Bainbridge, C., Torralba, A., & Oliva, A. (2015). Intrinsic and extrinsic effects on image memorability. *Vision Research*, *116*(Pt B), 165–178.
- Celikkale, B., Erdem, A., & Erdem, E. (2015). Predicting memorability of images using attention-driven spatial pooling and image semantics. *Image and Vision Computing*, *42*, 35–46.
- Craik, F. I. M., & Lockhart, R. S. (1972). Levels of processing: A framework for memory research. *Journal of Verbal Learning and Verbal Behavior*, *11*(6), 671–684.
- deBettencourt, M. T., Norman, K. A., & Turk-Browne, N. B. (2017). Forgetting from lapses of sustained attention. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-017-1309-5>
- deBettencourt, M. T., Williams, S. D., Vogel, E. K., & Awh, E. (2020). Sustained attention and spatial attention distinctly influence long-term memory encoding. *bioRxiv*. <https://doi.org/10.1101/2020.09.14.297341>
- Do Lam, A. T., Axmacher, N., Fell, J., Staresina, B. P., Gauggel, S., Wagner, T., ... Weis, S. (2012). Monitoring the mind: The neurocognitive correlates of metamemory. *PLOS ONE*, *7*(1), Article e30009. <https://doi.org/10.1371/journal.pone.0030009>
- Fleming, S. M., & Dolan, R. J. (2012). The neural basis of metacognitive ability. *Philosophical Transactions of the Royal Society of London: B, Biological Science*, *367*(1594), 1338–1349.
- Fukuda, K., & Woodman, G. F. (2015). Predicting and improving recognition memory using multiple electrophysiological signals in real time. *Psychological Science*, *26*(7), 1026–1037.
- Isola, P., Xiao, J., Parikh, D., Torralba, A., & Oliva, A. (2014). What makes a photograph memorable? *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *36*(7), 1469–1482.
- Kao, Y. C., Davis, E. S., & Gabrieli, J. D. (2005). Neural correlates of actual and predicted memory formation. *Nature Neuroscience*, *8*(12), 1776–1783.
- Khosla, A., Raju, A. S., Torralba, A., & Oliva, A. (2015). Understanding and predicting image memorability at a large scale. *2015 IEEE International Conference on Computer Vision (ICCV)* (pp. 2390–2398). <https://doi.org/10.1109/ICCV.2015.275>
- Koriat, A. (1997). Monitoring one's knowledge during study: A cue-utilization approach to judgments of learning. *Journal of Experimental Psychology: General*, *126*(4), 349–370.
- Light, L. L., Kayra-Stuart, F., & Hollander, S. (1979). Recognition memory for typical and unusual faces. *Journal of Experimental Psychology: Human Learning and Memory*, *5*(3), 212.
- Lin, Q., Yousif, S. R., Chun, M. M., & Scholl, B. J. (2021). Visual memorability in the absence of semantic content. *Cognition*, *212*, Article 104714.
- Lukavský, J., & Děchtěrenko, F. (2017). Visual properties and memorising scenes: Effects of image-space sparseness and uniformity. *Attention, Perception, & Psychophysics*, *79*(7), 2044–2054.
- Madan, C. R. (2021). Exploring word memorability: How well do different word properties explain item free-recall probability? *Psychonomic Bulletin & Review*, *28*(2), 583–595.
- Madan, C. R., Bayer, J., Gamer, M., Lonsdorf, T. B., & Sommer, T. (2017). Visual complexity and affect: Ratings reflect more than meets the eye. *Frontiers in Psychology*, *8*, Article 2368.
- McVay, J. C., Kane, M. J., & Kwapil, T. R. (2009). Tracking the train of thought from the laboratory into everyday life: An experience-sampling study of mind wandering across controlled and ecological contexts. *Psychonomic Bulletin & Review*, *16*(5), 857–863.
- Nelson, T. O., & Dunlosky, J. (1991). When people's judgments of learning (JOLs) are extremely accurate at predicting subsequent recall: The “delayed-JOL effect”. *Psychological Science*, *2*(4), 267–270.
- Noh, E., Herzmann, G., Curran, T., & de Sa, V. R. (2014). Using single-trial EEG to predict and analyze subsequent memory. *NeuroImage*, *84*, 712–723.
- Ovalle-Fresa, R., Uslu, A. S., & Rothen, N. (2021). Levels of processing affect perceptual features in visual associative memory. *Psychological Science*, *32*(2), 267–279.
- Rhodes, M. G. (2016). Judgments of learning: Methods, data, and theory. In J. Dunlosky & S. K. Tauber (Eds.), *The Oxford handbook of metamemory* (pp. 65–80). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199336746.013.4>
- Schwartz, B. L., & Metcalfe, J. (2017). Metamemory: An update of critical findings. In J. H. Bryne (Ed.), *Learning and memory: A comprehensive reference* (2nd ed., pp. 423–432). Academic Press. <https://doi.org/10.1016/B978-0-12-809324-5.21056-0>
- Smallwood, J. M., Baracaia, S. F., Lowe, M., & Obonsawin, M. (2003). Task unrelated thought whilst encoding information. *Consciousness and Cognition*, *12*(3), 452–484.
- Smallwood, J., Davies, J. B., Heim, D., Finnigan, F., Sudberry, M., O'Connor, R., & Obonsawin, M. (2004). Subjective experience and the attentional lapse: Task engagement and disengagement during sustained attention. *Consciousness and Cognition*, *13*(4), 657–690.
- Squalli-Houssaini, H., Duong, N. Q., Gwenaëlle, M., & Demarty, C. H. (2018, April). Deep learning for predicting image memorability. *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, (pp. 2371–2375). IEEE. <https://doi.org/10.1109/ICASSP.2018.8462292>
- Standing, L. (1973). Learning 10,000 pictures. *Quarterly Journal of Experimental Psychology*, *25*(2), 207–222.
- Sundby, C. S., Woodman, G. F., & Fukuda, K. (2019). Electrophysiological and behavioral evidence for attentional up-regulation, but not down-regulation, when encoding pictures into long-term memory. *Memory & Cognition*, *47*(2), 351–364.
- Torralba, A., & Oliva, A. (2003). Statistics of natural image categories. *Network: Computation in Neural Systems*, *14*(3), 391.
- Tozios, C. J. I., & Fukuda, K. (2019). Indirect, but not direct, down-regulation of visual long-term memory encoding through strategic biasing of attentional allocation. *Journal of Experimental Psychology: General*. <https://doi.org/10.1037/xge0000712>
- Wagner, A. D., Schacter, D. L., Rotte, M., Koutstaal, W., Maril, A., Dale, A. M., ... Buckner, R. L. (1998). Building memories: Remembering and forgetting of verbal experiences as predicted by brain activity. *Science*, *281*(5380), 1188–1191. <https://doi.org/10.1126/science.281.5380.1188>

- Xie, W., Bainbridge, W. A., Inati, S. K., Baker, C. I., & Zaghoul, K. A. (2020). Memorability of words in arbitrary verbal associations modulates memory retrieval in the anterior temporal lobe. *Nature Human Behavior*, 4(9), 937–948.
- Yang, H., Cai, Y., Liu, Q., Zhao, X., Wang, Q., Chen, C., & Xue, G. (2015). Differential neural correlates underlie judgment of learning and subsequent memory performance. *Frontiers in Psychology*, 6, Article 1699.

**Publisher's note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.