Running Head: PRESTIMULUS CUES BENEFIT RECOGNITION MEMORY

Informative and uninformative prestimulus cues at encoding benefit familiarity and source memory

Nicholas Yeh and Joshua D. Koen*

Department of Psychology, University of Notre Dame, IN

*Corresponding Author:

Joshua D. Koen

University of Notre Dame

Department of Psychology

Notre Dame, IN 46556

Email: jkoen@nd.edu

Abstract

Previous research has shown that neural activity elicited by informative prestimulus cues during encoding differ with respect to subsequent memory outcomes. These findings have been taken as evidence that prestimulus cues benefit processes associated with successful encoding and, ultimately, subsequent memory performance. However, previous studies have not included the conditions necessary to appropriately test this assumption. We address this shortcoming by examining how informative and uninformative prestimulus encoding cues affect memory accuracy for upcoming stimuli compared to a no cue condition. At encoding, participants made one of two semantic judgments on words preceded by an informative prestimulus cue that identified the upcoming semantic judgment, an uninformative prestimulus cue that signaled an upcoming trial but no information about the semantic judgment, or no cue. Dual process estimates of familiarity, but not recollection, demonstrated a graded pattern with the informativeness of the prestimulus cues (i.e., informative > uninformative > no cues). Moreover, both informative and uninformative prestimulus cues enhanced subsequent source memory accuracy for the encoding task compared to the no cue condition. These findings suggest that prestimulus cues can strengthen the processes that support successful memory encoding and benefit subsequent familiarity and source memory.

Keywords: Recognition Memory, Dual Process Theory, Encoding, Attention, Prestimulus Subsequent Memory Effects

Introduction

Efforts to understand how new experiences are encoded into memory have focused on the cognitive and neural processes elicited in the period immediately after the experience of an event. Most studies examining the neural correlates of successful encoding have used the subsequent memory procedure (Wagner et al., 1998) to investigate differences in neural activity elicited by stimuli that are later remembered or forgotten (Kim, 2011). However, there is now compelling evidence that ongoing neural activity elicited by a prestimulus cue in the seconds or so *prior to* the presentation of a stimulus is associated with subsequent memory outcomes (e.g., de Chastelaine & Rugg, 2015; Gruber & Otten, 2010; Otten et al., 2006, 2010; for review, see N. Cohen et al., 2015). In other words, neural activity elicited by prestimulus cues at encoding differs in magnitude when the stimulus following the cue is remembered or forgotten (i.e., differences in subsequent memory outcomes). An interesting implication from these findings is whether prestimulus cues enhance memory accuracy of the upcoming stimulus. This has not been directly tested because prior EEG and fMRI studies have focused on the neural activity elicited by a single prestimulus cue that conveys something *informative* about the upcoming stimulus, but not how informative prestimulus cues benefit subsequent memory performance. Additional prestimulus cue conditions, such as an *uninformative* prestimulus cue or a *no cue* condition, are needed to understand so-called pre-stimulus subsequent memory effects more fully and how prestimulus cues affect subsequent memory performance (e.g., memory discriminability on subsequent tests). Therefore, our aim here is to expand on these neuroimaging findings to examine if prestimulus cues during encoding enhance later memory performance.

Research examining prestimulus subsequent memory effects – differences in neural activity preceding the onset of a to-be-remembered stimulus as a function of subsequent memory – have concentrated on neural activity elicited by prestimulus cues at encoding that conveyed something informative about an aspect of the upcoming trial (Adcock et al., 2006; Addante et al., 2015; Bollinger et al., 2010; de Chastelaine & Rugg, 2015; Fellner et al., 2013; Galli et al., 2012; Gruber & Otten, 2010; Koen, Horne, et al., 2018; Liu et al., 2021; Mackiewicz et al., 2006; Otten et al., 2006; Park & Rugg, 2010). For instance, Otten and colleagues (2006) recorded event-related potentials elicited by informative prestimulus cues that instructed participants to make a semantic or orthographic judgment about an upcoming word. Using the Remember/Know procedure (Tulving, 1984), the authors observed negative going event-related potentials at frontal scalp electrodes elicited by cues preceding words that attracted subsequent Remember responses relative to words attracting subsequent Know and New responses (also see Otten et al., 2010; for related fMRI findings, see de Chastelaine & Rugg, 2015; Park & Rugg, 2010). These findings were taken to suggest that prestimulus subsequent memory effects are associated with recollection. Additional studies have provided converging evidence that prestimulus subsequent memory effects are associated with subsequent recollection, including tasks using more objective measures of recollection such as source (Koen, Horne, et al., 2018; Liu et al., 2021) and associative memory (Addante et al., 2015). Moreover, prestimulus subsequent memory effects have been observed in the hippocampus (Addante et al., 2015; de Chastelaine & Rugg, 2015;

Guderian et al., 2009; Liu et al., 2021; Merkow et al., 2014; Park & Rugg, 2010; Uncapher et al., 2011), a region that plays an important role in recollection (for reviews, see Diana et al., 2007; Eichenbaum et al., 2007; Yonelinas et al., 2010). While these data provide a link between prestimulus subsequent memory effects and subsequent recollection (see also Salari & Rose, 2016), it remains an open question as to whether informative prestimulus cues during encoding are associated with selective increases in behavioral estimates of recollection or broader effects on recognition memory.

The findings discussed above predict that providing informative prestimulus cues during encoding will benefit the processes supporting successful memory encoding and, in turn, benefit measures of subsequent memory performance such as memory discrimination or estimates of recollection and familiarity. However, this prediction has not been directly assessed by the neuroimaging literature. First, simply observing prestimulus subsequent memory effects in neural activity in a single condition (i.e., informative prestimulus cues) does not indicate that such activity will lead to better (or worse) levels of memory performance. Second, and more importantly, neuroimaging studies have typically not included the conditions necessary to test the above hypothesis. For instance, most studies have included informative prestimulus cues (e.g., cues indicating a semantic or orthographic judgment about a word) but have not included a critical comparison condition that includes either an uninformative cue (e.g., neutral cues signaling a trial is upcoming but provides no information about performing a semantic or orthographic judgment about a word) or no prestimulus cue at all. The few studies that have included multiple types of cues have found that informative cues enhance memory compared to uninformative cues (Bollinger et al., 2010; although see Lin et al., 2017) and no prestimulus cues (Lin et al., 2015). However, these studies did not parse out different mnemonic processes, namely recollection and familiarity, which might be critical to understanding how different types of prestimulus encoding cues influence subsequent memory performance. Another related body of work examining the role of schemas and expectations on memory encoding have demonstrated that valid cues that accurately predict a feature of the upcoming stimulus (e.g., a natural or manmade object) facilitate familiarity whereas invalid cues enhance recollection (Kafkas, 2021; Kafkas & Montaldi, 2018; but see, Uncapher et al., 2011). The above studies also differ from prior neuroimaging work in that the prestimulus cues were not required to successfully complete the encoding task (but see, Galli et al., 2012; Gruber & Otten, 2010; Otten et al., 2006, Experiment 2). The findings discussed above provide some evidence that prestimulus encoding cues benefit memory performance in some conditions. However, it remains an open question if these behavioral findings extend to paradigms that have been shown to elicit prestimulus subsequent memory effects observed in EEG and fMRI data, and if the memory benefits associated with informative prestimulus cues are more strongly associated with recollection and familiarity.

Additionally, identifying when and under what circumstances different types of prestimulus cues at encoding benefit later memory accuracy will provide valuable theoretical insights about prestimulus subsequent memory effects observing EEG and fMRI studies, which,

as discussed above, have only included informative prestimulus cues. Of relevance to the present investigation are two hypotheses of prestimulus subsequent memory effects from the neuroimaging literature initially proposed by Otten and colleagues (2006; see also, Adcock et al., 2006; Park & Rugg, 2010). One possibility is that informative and uninformative prestimulus cues relative to no prestimulus cues enhance memory accuracy with no memory differences emerging between the two prestimulus cues. This finding would align with a general attention hypothesis that prestimulus cues recruit general attentional resources that benefit memory encoding processes. A second possibility is that informative prestimulus cues, relative to both uninformative prestimulus cues and no prestimulus cues, enhances memory accuracy with no differences between uninformative and no prestimulus cues. If informative prestimulus cues proactively engage in task specific preparatory processes, this finding would align with a task set hypothesis. This hypothesis argues that prestimulus cues orient individuals to adopt an optimal task set through conscious, flexible, and strategic processes, which in turn benefits encoding of trials for which the task set is more effectively deployed in the prestimulus interval. It is important to point out that the general attention and task set hypotheses are not mutually exclusive.

The present investigation examined whether informative and uninformative prestimulus cues during encoding benefited recognition memory performance relative to when no prestimulus cues were presented. For the purposes of improving our ability to relate these findings to the prestimulus subsequent memory effect literature discussed above, we used a modified version of an experimental procedure from our prior work (Koen, Horne, et al., 2018; Liu et al., 2021) that included informative cues, uninformative cues, and no prestimulus cues across four experiments (see Figure 1). At test, participant made recognition memory decision using a 6-point confidence that allowed for multiple measures of memory to be computed. We included the analysis of corrected hit rates for comparison with prior behavioral work (e.g., Bollinger et al., 2010; Lin et al., 2015, 2017). Moreover, old/new recognition decisions were acquired using a 6-point confidence scale to allow us to measure of recollection and familiarity with the dual-process signal detection model (Koen et al., 2017; Yonelinas, 1999; for reviews, see Yonelinas et al., 2010; Yonelinas & Parks, 2007). This allowed us to examine whether prestimulus cues differentially affected these two qualitatively distinct mnemonic processes. In addition, for Experiments 2-4, we included an objective measure of recollection (i.e., source memory for the semantic judgments made during encoding) to further explore whether prestimulus encoding cues affect recollection. Source memory was chosen because prestimulus subsequent memory effects have been shown to vary with source memory outcomes (e.g., correct vs. incorrect) in the neuroimaging work motivating this investigation (Koen, Thakral, et al., 2018; Liu et al., 2021).

Given the similarity in the experimental designs and measures across all four experiments, we collated the data across relevant measures in each of the experiments and performed a linear mixed effects regression analysis. This approach helps to maximize the statistical power by pooling the data from all four experiments, while also accounting for error

variance across experiments and participants. While this across-experiment analysis was not pre-registered, and thus should be considered exploratory, it closely follows the pre-registered analysis plan from each experiment.

Methods

Ethics statement

These studies were approved by the Institutional Review Board of the University of Notre Dame. All participants provided informed consent before participation.

Preregistrations and Data Availability

We pre-registered the exclusion criteria, hypotheses, and analyses for each of the four experiments on the Open Science Framework. The pre-registrations, sample size justification, and data (both raw and derived) for each individual experiment, and for the across experiment analysis reported here, can be obtained on the Open Science Framework (<https://osf.io/ydmun/>).

Participants

A total of 560 individuals were recruited to participate in one of four experiments. A total of 424 participants (234 females, 187 males, 3 preferred to not answer, $M_{\text{age}} = 22.71$, 18-30 years of age) contributed data to the across experiment analyses reported here. This sample comprised 64, 82, 130, and 148 participants from Experiments 1-4 respectively. Note that data from an additional 136 participants were collected and excluded from the analysis due to meeting one of the pre-registered exclusion criteria. Exclusionary criteria included failing to respond on 20% or more of either the encoding trials or test trials, low item memory ($<.10$), low source memory ($<.05$), and responding with the middle range of the confidence responses (i.e., 2-5 bins) on fewer than 10% of all valid test trials (collapsed across all trial types). For full breakdown of the number of participants excluded based on these criteria, see Supplemental Table S1.

All participants were young adults fluent in English with no reported history of color blindness. In Experiment 1, participants also reported no history of memory disorders or severe head injuries. Participants were recruited for in-person testing (Experiment 1) and online testing (Experiment 2) from the University of Notre Dame's online recruitment system (SONA). Additionally, fourteen participants in Experiment 2, and all participants in Experiment 3-4, were recruited from online crowd sourcing platform Prolific (<https://www.prolific.co/>). Participants recruited from Prolific had an approval rating of 90% or greater (e.g., participant's performance metric for completing Prolific studies). This Prolific guideline is consistent with previous work (Peer et al., 2014). In addition, individuals who participated in one of the studies were ineligible to partake in the others. Participants for the four experiments were compensated either with course credit or \$10.00 if they were recruited through the University of Notre Dame or through Prolific, respectively.

Materials and Apparatus

The stimuli comprised of 384 nouns for Experiments 1-2 and 450 nouns for Experiments 3-4). The words were obtained from the MRC Psycholinguistic Database (Coltheart, 1981) with the following characteristics: 4-8 ($M = 5.37$, $SD = 1.20$) letters in length, ranged from 1-40 ($M = 12.81$, $SD = 10.05$) in written frequency (Kučera & Francis, 1967), and had concreteness ratings in the range of 500-662 ($M = 582.94$, $SD = 31.83$). An additional 45 words with similar characteristics were used to make practice encoding and test lists.

For Experiment 1, we created a randomly generated stimulus list for each participant comprised of 256 words the encoding phase (128 words the informative and uninformative conditions) with the remaining 128 words (new) being presented during the recognition test. For Experiment 2, the stimuli were the same as in Experiment 1 with the exception that 8 stimulus sets were pseudo randomly generated to match informative vs. no cue conditions (128 words in each condition) on the same word characteristics (length, frequency, and concreteness.) In Experiments 3 and, 66 additional words were added to the words from Experiments 1 and 2 and were used to create 4 stimuli sets with 300 words assigned to the study phase and 150 words assigned to be new items at test. The lists were created pseudorandomly matching the informative, uninformative, and no cue conditions (100 words in each condition) on the same word characteristics.

The stimuli for Experiment 1 was presented using PsychoPy v3.0.3 (Peirce, 2007; Peirce et al., 2019). The words were presented in Helvetica font at a height of 1.5 degrees of visual angle (using PsychoPy *degFlat* units). For Experiments 2-4, the stimuli were presented via Pavlovia.org using PsychoPy v2020.1.3 (Peirce, 2007; Peirce et al., 2019). Words were presented in white, teal, or red Arial font with a letter height of .05 (using *height* units) on a grey background.

Procedure

Across the four experiments the participants completed an incidental encoding task and recognition test. Experiments 2-4 included a source memory judgment for words attracting an old response. The recognition test occurred either immediately (Experiments 2-4) or 10 minutes (Experiment 1) following the encoding phase.

Encoding phase

During the incidental encoding phase, participants made one of two semantic judgments (shoebox, manmade) for each word. For the manmade judgments, participants responded ‘yes’ if the word denoted a manmade object, and ‘no’ if the word denoted a natural object. For the shoebox judgment, participants responded ‘yes’ if the object denoted by the word fit inside a shoebox, and ‘no’ otherwise. Participants were instructed to enter their keyboard responses (i.e., “j” yes and “k” for no) quickly and with high accuracy.

There were three different prestimulus cue conditions across the four experiments (informative, uninformative, or no cues). Informative cues signaled whether participants should make a manmade judgment (blue shape) or shoebox judgment (red shape) for upcoming words. Uninformative cues consisted of a white shape which signaled an upcoming trial without any semantic judgment information to be performed on the word. In this case, the semantic judgment was signaled simultaneously with the word (e.g., inside a blue or red box). The no prestimulus cue trials did not provide any information about the upcoming trial or the semantic judgment. The semantic judgment was signaled in the same way as in the uninformative cue trials.

In general, each trial was comprised of the presentation of a prestimulus cue (informative, uninformative, or no cue), a fixation cross, a word, and a final fixation cross (see Figure 1 for trial timing for each experiment). The response window included the time between the onset of a word and the final fixation cross. Participants completed a short practice phase before the critical encoding phase.

Experiment 1 presented informative and uninformative cues pseudorandomly and intermixed such that no more than 3 trials with the same cue condition or semantic judgment occurred consecutively. Experiment 2 presented informative and no prestimulus cues in a blocked design (2 informative, 2 no cue) with an ABBA/BAAB counterbalance scheme (A-informative, B- no cue). Experiment 3 presented all three cue conditions with a blocked design using an ABCCBA/BCAACB/CABBAC counterbalance scheme (A-informative, B-uninformative, C-no cue). Experiment 4 presented all three prestimulus cue conditions randomly intermixed in the same phase.

Figure 1. Depiction of the encoding task structure and trials timing for Experiments 1-4. Participants made semantic judgments (shoebox, manmade) about words preceded by either informative, uninformative, or no cues. Informative cues indicated ahead of time what semantic judgment to make for the words, with red and blue shapes signaling a shoebox and manmade judgment respectively. Uninformative cues, which were signaled by a white shape, indicated that a trial was upcoming but contained no information regarding the semantic judgment to make.

Instead, the semantic judgment was signaled simultaneously with the word by either a red/blue font (Experiment 1) or red/blue box containing the word (Experiment 2-4). No cues contained no information about the upcoming trial or semantic judgment to make. For these trials, the semantic judgment was signaled in the same manner as the uninformative cue trials. The response window for the semantic judgments began with the word presentation and for the duration of the fixation cross following word presentation. Note, Experiment 4 included a 1-2s jitter following the response window time. Experiment 1 and 4 presented prestimulus cues intermixed. Experiment 2 and 3 presented prestimulus cues in individual blocks.

Recognition test

Following the encoding phase, participants completed a recognition memory test in which they identified studied words as “old” and words not presented in the encoding phase as “new” using a 6-point confidence scale (i.e., “1-sure new”, “2- maybe new”, “3-guess new”, “4-guess old”, “5-maybe old”, “6-sure old”) (Yonelinas & Parks, 2007). Participants were instructed to use the full range of confidence scale responses to accurately report their confidence in their memory judgment. In Experiments 2-4, following an old response (i.e., a 4, 5, or 6 confidence response), participants made a source memory decision by reporting their memory for the semantic judgment performed on the word during the encoding phase (i.e., shoebox, manmade, or don’t know). Participants were instructed to select the shoebox or manmade judgment response if they could remember which semantic judgment was paired with the word during the encoding phase, otherwise they were instructed to respond with a “Don’t Know” response. A “new” response (i.e., a 1, 2, or 3 confidence response) progressed the task to the next test item. In Experiment 1, the words were presented pseudorandomized (i.e., so that no more than three trials from the same condition occurred consecutively) with the old/new responses being self-paced keyboard responses. In Experiments 2-4, the words were presented randomly with both the old/new and source memory touchpad/mouse responses having a 10 sec time limit. There was a .5 second inter-trial interval of after the last response (item or source memory response). Participants completed a practice test phase prior to the main recognition test to ensure they understood the instructions.

Dependent variables

Corrected hit rates (i.e., hits – false alarms) were computed for each condition to comparable measures to previous studies (Bollinger et al., 2010; Lin et al., 2015, 2017). The hit rates were determined as the proportion of ‘old’ responses, regardless of confidence, to old items. The false alarm rate was computed as the proportion of ‘old’ responses to new items. Note that there was only a single new item condition. Thus, any differences between corrected hit rates across the different cue conditions must be driven by differences in the hit rates. We report the data as corrected hit rates for consistency with prior work.

Recollection and familiarity were estimated by fitting the dual-process signal detection model to receiver operating characteristics from confidence responses. Model fitting was carried out using the ROC Toolbox for Matlab (Koen et al., 2017) using the dual-process signal detection model. Our choice to use this model (Yonelinas, 1994, 1999) was driven by findings linking prestimulus subsequent memory effects to recollection (e.g., Otten et al., 2006, 2010; Park & Rugg, 2010) and based on prior work demonstrating that the parameters of the dual-process signal detection model behave in a theoretically meaningful way (Koen et al., 2013; Koen & Yonelinas, 2010, 2011; Yonelinas, 1999, 2001). The dual-process signal detection model estimates recollection as a probability ranging from 0 to 1 and familiarity as a discrimination index (d'); familiarity estimates were constrained to be positive (i.e., > 0). For Experiments 1 and 2, the model fitting routine estimated a total of 9 parameters: two estimates of recollection (informative and uninformative cues in Experiment 1; informative and no cue in Experiment 2), two estimates of familiarity, and five parameters modeling the location of response criterion. For Experiments 3 and 4, the model fitting routine estimated a total of 11 parameters: three estimates of recollection (informative, uninformative, no cue), three estimates of familiarity (informative, uninformative, no cue), and five parameters modeling the location of response criterion. The number of criterion parameters for confidence-based receiver operating characteristics is always $N-1$, where N is the number of confidence bins. The same criterion parameters were used for the informative, uninformative, and no cue conditions because there was only a single set of new items.

Additionally, source memory performance was computed for Experiments 2-4 accounting for the “guess rate” using a single high threshold model (Mattson et al., 2014; Snodgrass & Corwin, 1988). For correctly recognized old words (i.e., old words attracting a ‘sure old’, ‘maybe old’, and ‘guess old’ response), the proportion of correct source memory responses (Hit) and the proportion of “don’t know” (DK) source responses were used to calculate source memory accuracy (i.e., probability of source recollection; pSR) with the following formula:

$$pSR = \frac{Hit - .5 * [1 - DK]}{1 - .5 * [1 - DK]}$$

Statistical Analyses

The statistical analyses comprised of a series of linear mixed effects regression models conducted on the dependent measures extracted from the four experiments. The linear mixed effects regression approach has several advantages over traditional ANOVA analyses, such as modeling a nested structure (e.g., participants within experiments), handling missing observations (e.g., experiments not including all cue conditions or all memory measures), and appropriately accounting for random effects (e.g., participants varying in memory performance for the cue conditions across experiments). The mixed effects analyses were conducted in R

(version 3.6.3) with the *mixed* function in the *afex* package (Singmann et al., 2021) and follow up post hoc tests being carried out with the *emmeans* package (Lenth, 2021). These models had a single fixed effect factor of cue condition (informative, uninformative, no cue). There were also two random intercepts for participants and experiment, with participants nested within experiments. The mixed effects model formula was:

$$Memory_{ij} = \beta_{00} + \beta_{01}cue\ condition_{ij} + \left(z_{Experiment_i} / u_{Participant_j} \right)$$

In the above equation, $Memory_{ji}$, represents the predicted memory measure for Participant j and Experiment i , β_{00} is the model intercept, the beta coefficient (β_{01}) represent the fixed effect of cue condition, $z_{Experiment_i} / u_{Participant_j}$ represents that Participant j is nested within Experiment i . A separate mixed effects analysis was carried out for each of the four dependent measures: corrected hit rates, familiarity estimates, recollection estimates, and source memory (pSR). Degrees of freedom for the fixed effects were estimated with the Kenward-Roger method. We report effects sizes of partial-eta squared (η_p^2) for the main effects of cue condition and, where appropriate, Cohen's d for post-hoc comparisons (J. D. Cohen, 1988). The 95% confidence interval of the effect sizes are also reported.

Results

The analyses reported below focus on corrected hit rates, the familiarity and recollection estimates derived from receiver operating characteristics curves, and on estimates of source memory accuracy. The proportion of responses in each confidence bin and source memory classification for the different item types are shown in Table 1 and 2, respectively.

Table 1. Mean (and SD) of confidence responses for old (Informative, Uninformative, and No cue) and new words.

Item Type	Confidence Bin					
	Sure New	Maybe New	Guess New	Guess Old	Maybe Old	Sure Old
Informative	.05 (.07)	.09 (.08)	.10 (.09)	.09 (.08)	.15 (.11)	.52 (.23)
Uninformative	.05 (.07)	.09 (.07)	.10 (.09)	.08 (.08)	.15 (.11)	.53 (.23)
No cue	.07 (.08)	.10 (.08)	.11 (.10)	.10 (.09)	.15 (.11)	.47 (.22)
New	.29 (.21)	.29 (.14)	.23 (.16)	.07 (.06)	.06 (.06)	.05 (.06)

Note. Item responses were made on a 6-point scale (1 = sure new, 2 = maybe new, 3 = guess new, 4 = guess old, 5 = guess old, 6 = sure old). Item responses proportions were calculated for

each item response category. The sample size contributing to these means were 424, 342, 360, and 424 for the Informative, Uninformative, No cue, and New item types, respectively.

Table 2. Mean (and SD) of the proportion of the different source memory classifications for old trials (Informative, Uninformative, and No cue) receiving a correct ‘sure old’, ‘maybe old’, or ‘guess old’ responses.

Item Type	Source Memory Classification		
	Source Correct	Source Incorrect	Source Don’t know
Informative	0.53 (.18)	0.13 (.07)	0.09 (.10)
Uninformative	0.53 (.17)	0.13 (.07)	0.09 (.10)
No cue	0.50 (.17)	0.13 (.07)	0.09 (.10)

Note. For the source memory judgments participants responded with whether the old item was encoded with a shoebox or manmade response, and a Don’t know response if they were not sure what semantic judgment they made. Proportions were collapsed across the semantic judgment trial types and responses. The sample size contributing to these means were 360, 278, and 360 for the Informative, Uninformative, No Cue trial types, respectively.

The conclusions we reached based on the analyses reported below were unchanged with an exploratory analysis that used the reverse Bonferroni method (Francis & Thunell, 2021) with the analysis of each experiment individually. This approach controls for Type 1 and 2 error rates by adjusting the alpha criterion level upwards ($\alpha = .05^{1/k}$; k = number of tests within a family of comparisons) when drawing conclusions that require consistent results across direct and conceptual replications (i.e., all results are significant in each experiment) to support a hypothesis. This exploratory analysis, as well as the pre-registered planned analyses of memory performance and encoding reaction times for each experiment, are reported in the Supplemental Materials.

Corrected hit rates

The linear mixed effects regression analysis on the corrected hit rates revealed a significant cue condition effect, $F(2, 700.86) = 27.94, p < .001, \eta_p^2 = .07$ [95% CI: .04, .11] (see Figure 2). Post-hoc tests demonstrated that corrected hit rates were higher for words preceded by informative, $t(701.59) = 7.42, p < .001, d = .56$ [95% CI: .41, .71], and uninformative prestimulus cues, $t(701.45) = 4.68, p < .001, d = .35$ [95% CI: .20, .50], relative to no prestimulus cues. Corrected hit rates were also higher for words preceded by informative relative to uninformative prestimulus cues, $t(701.66) = 2.27, p = .024, d = .17$ [95% CI: .02, .32]. These results demonstrate a ‘graded’ pattern with informative prestimulus cues being associated with

the highest corrected hit rates and no prestimulus cues being associated with the lowest corrected hit rates.

Figure 2. Results for the corrected hit rates. Left panel displays raincloud plots. The boxplots show the median, notches (95% confidence intervals), and the interquartile (IQR) with lower and upper whiskers ($1.5 * \text{IQR min and max}$). The means of the left panel reflect the model implied mean and 95% confidence interval. The right panel displays the violin plots for corrected hit rate difference scores between the three cued conditions along with the model implied mean differences and 95% confidence interval.

Dual Process Signal Detection Model Parameter Estimates

Familiarity

The results from the linear mixed model conducted on familiarity estimates also demonstrated a significant effect of cue condition, $F(2, 703.90) = 20.27, p < .001, \eta_p^2 = .05$ [95% CI: .03, .09] (see Figure 3). Post-hoc contrasts demonstrated a graded effect across the three cue conditions (i.e., informative > uninformative > no cue). Specifically, familiarity estimates were significantly higher for words preceded by informative, $t(705.87) = 6.37, p < .001, d = .48$ [95% CI: .33, .63], and uninformative prestimulus cues, $t(703.91) = 3.28, p = .001, d = .25$ [95% CI: .10, .40], relative to no prestimulus cues. Familiarity estimates were also higher for words preceded by informative prestimulus encoding cues relative to uninformative prestimulus encoding cues, $t(704.20) = 2.73, p = .007, d = .21$ [95% CI: .06, .35].

Figure 3. Results for the familiarity estimates. Left panel displays raincloud plots. The boxplots show the median, notches (95% confidence intervals), and the IQR with lower and upper whiskers ($1.5 * \text{IQR min and max}$). The means of the left panel reflect the model implied mean and 95% confidence interval. The right panel displays the violin plots for corrected hit rate difference scores between the three cued conditions along with the model implied mean differences and 95% confidence interval.

Recollection

There was no significant effect of cue condition on estimates of recollection derived from the dual process signal detection model, $F(2, 700.81) = 27.94, p < .001, \eta_p^2 = .01$ [95% CI: .00, .05] (see Figure 4).

Figure 4. Results for the recollection estimates. Left panel displays raincloud plots. The boxplots show the median, notches (95% confidence intervals), and the IQR with lower and upper whiskers ($1.5 * \text{IQR min and max}$). The means of the left panel reflect the model implied mean and 95% confidence interval. The right panel displays the violin plots for corrected hit rate difference scores between the three cued conditions along with the model implied mean differences and 95% confidence interval.

Source Memory (pSR)

The results from the linear mixed effects regression analysis on source memory (i.e., pSR) revealed a significant effect of cue condition, $F(2, 637.77) = 6.72, p < .001, \eta_p^2 = .02$ [95% CI: .00, .05] (see Figure 5). This effect was driven by source memory performance being higher for words preceded by informative, $t(636.09) = 3.14, p = .002, d = .25$ [95% CI: .09, .41], and uninformative prestimulus cues, $t(638.62) = 3.11, p = .002, d = .25$ [95% CI: .09, .40], relative to the no prestimulus cue condition. The difference in source memory accuracy between informative and uninformative prestimulus cues was not significant, $t(638.62) = .27, p = .788, d$

= .02 [95% CI: -.18, .13]. These results suggest that source memory for the semantic judgment was enhanced for words preceded by both informative and uninformative prestimulus cues.

Figure 5. Results for source memory. Left panel displays raincloud plots. The boxplots show the median, notches (95% confidence intervals), and the IQR with lower and upper whiskers ($1.5 \times$ IQR min and max). The means of the left panel reflect the model implied mean and 95% confidence interval. The right panel displays the violin plots for corrected hit rate difference scores between the three cued conditions along with the model implied mean differences and 95% confidence interval.

Discussion

The present study investigated whether informative prestimulus cues, uninformative prestimulus cues, or no cues influenced overall recognition memory performance as well as measures of different mnemonic processes. The primary finding from the across-experiment analysis was that both informative and uninformative prestimulus cues compared to the no cue condition enhanced memory performance in a graded fashion. Specifically, words encoded with

an informative prestimulus cue had the highest corrected hit rates compared to both uninformative and no prestimulus cues, and words encoded with uninformative prestimulus cues had higher corrected hit rates compared to the no prestimulus cue condition. The pattern of memory enhancements for informative and uninformative cues also appeared to depend on the mnemonic process. First, like corrected hit rates, familiarity estimates accuracy showed a graded effect with the informativeness of the prestimulus cues. Second, although there was no effect of prestimulus cues on estimates of recollection derived from the dual process signal detection model, we observed that, relative to the no cue condition, informative and uninformative prestimulus cues benefited source memory performance, which can be considered an objective measure of recollection. Source memory, however, did not differ between informative and uninformative prestimulus cues.

To our knowledge, the present work is first to simultaneously examine potential memory enhancements of informative, uninformative, and no prestimulus cues on multiple memory measures (i.e., corrected hit rates, familiarity, recollection, and source memory). Our findings expand on prior studies examining the influence of prestimulus cues on memory with at most two types of cues, such as informative vs. no prestimulus cues (Lin et al., 2015) and informative vs. uninformative prestimulus cues (deBettencourt et al., 2021; Kafkas, 2021; Kafkas & Montaldi, 2018). For example, Lin and colleagues (2015) had participants encode scenes that were preceded by either an informative prestimulus cue that signaled the valence of the upcoming scene (i.e., X = negative, O = neutral) or no prestimulus cue. The authors found that informative prestimulus cues compared to no prestimulus cues enhanced recognition memory (i.e., hit rates for scenes) on an old/new recognition test. Our inclusion of informative, uninformative, and no prestimulus cues go beyond these prior studies to show a graded effect on memory performance as a function of the informativeness of the prestimulus cues. Taken together, the findings suggest that all prestimulus cues may not be associated with the same memory enhancements and that degree to which prestimulus cues can enhance memory may be related the informativeness of the prestimulus cue.

Our results also converge with prior studies and demonstrate the graded effect of cue informativeness may depend on the specific mnemonic processes being measured. Here, we found the graded effect of prestimulus cue type on estimates of familiarity. Prior research by Kafkas and colleagues (Kafkas, 2021; see also Kafkas & Montaldi, 2018) compared estimates of familiarity between valid and invalid prestimulus cues that signaled whether participants should expect to see an image of a natural or manmade object. A subsequent memory test revealed that objects preceded by valid cues (i.e., cues that signaled the correct category) at encoding were associated with higher familiarity estimates relative to objects preceded invalid cues (i.e., cues that incorrectly signal an upcoming image category). It is important to point out that while the valid cues used by Kafkas and colleagues were like our informative prestimulus cues, the invalid cues differ from the uninformative cues used in our study. Specifically, the invalid cues in Kafkas and colleagues signal something incorrect about the upcoming trial, whereas our uninformative cues simply signaled the trial was about to appear but did not carry any additional

information. It remains an open question if invalid cues like those used by Kafkas and colleagues would also enhance familiarity estimates relative to a condition with no prestimulus cues. Such a finding would converge with our results reported here and provide additional evidence that the informativeness of prestimulus cues during encoding is associated with a monotonic increase in familiarity estimates (and likely overall memory performance) on a subsequent memory test.

Our findings also provide valuable context for EEG/ERP and fMRI studies (de Chastelaine & Rugg, 2015; Koen, Horne, et al., 2018; Liu et al., 2021; Otten et al., 2006) typically correlated the neural activity elicited by an informative prestimulus cue prior to encoding with subsequently remembered or forgotten responses. As discussed in the Introduction, the predominate assumption from these neuroimaging findings is that the prestimulus neural activity elicited by the informative prestimulus cues reflect encoding processes that support subsequent recollection. Our findings here can more readily speak to prior neuroimaging studies as we used a variation of a task used to examine prestimulus subsequent memory effects in neural activity (Koen, Horne, et al., 2018; Liu et al., 2021). The reported results are not fully consistent the proposal that prestimulus subsequent memory effects are selectively associated with subsequent recollection-based memory. First, we only observed that prestimulus cues enhanced objective (source memory), but not subjective, measures of recollection. In other words, the recollection effect we observed appeared to be selective to the cued information (i.e., the encoding judgment) and not more general. Second, and more importantly, we found that prestimulus cues also affected estimates of familiarity (for related findings, Kafkas, 2021; Kafkas & Montaldi, 2018). Prior neuroimaging research may have missed the relationship between prestimulus subsequent memory effects and familiarity because they have not clearly isolated recollection from familiarity. For example, previous findings have contrasted neural activity associated with subsequent Remember responses from that associated with a combination of subsequent Know and New responses (e.g., Otten et al., 2006). Although some work has, arguably, more clearly linked prestimulus subsequent memory effects to recollection (e.g., de Chastelaine & Rugg, 2015; Otten et al., 2010; Park & Rugg, 2010), the links to familiarity have not been thoroughly investigated. These findings provide evidence the prestimulus cues are associated with both recollection and familiarity and motivate future neuroimaging that more thoroughly investigates prestimulus subsequent memory effects associated with familiarity.

Our results also have implications for two accounts of prestimulus subsequent memory effects reported in neuroimaging studies, namely the task set and general attention hypotheses. The results from the analysis of familiarity estimates are most consistent with the task set hypothesis. This hypothesis proposes that prestimulus cues orient individuals to engage an optimal task set through conscious, flexible, and strategic processes. Adoption of these proactive processes are proposed to benefit encoding of trials for which the task set is more effectively deployed in the prestimulus interval (Otten et al., 2006, 2010). We argue the task set hypothesis predicts that more informative cues will increase the likelihood of adopting the appropriate task set, and thus will have the largest benefit to subsequent memory performance, which is broadly

consistent with the pattern of results we observed for familiarity estimates. However, familiarity showed a graded relationship with the prestimulus encoding cue condition (i.e., informative > uninformative > no cue; see Figure 3). A strict interpretation of this hypothesis, we argue, predicts that only informative cues would benefit subsequent memory performance. Thus, it is unclear if this finding is actually consistent with the task set hypothesis. However, the task set and general attention hypotheses are not mutually exclusive. One way to reconcile the prestimulus subsequent memory findings with respect to our familiarity findings is to assume that the effects of activating a task set and general attention resources are additive. Given this assumption, one would expect a graded effect whereby informative prestimulus cues benefit memory encoding compared to uninformative prestimulus cues which, in turn, leads to better memory performance compared to trials with no prestimulus encoding cues. Future work is needed to examine the implications of these findings more fully.

The source memory findings are most consistent with the hypothesis that prestimulus cues recruit general attentional resources that are beneficial for memory encoding. In the context of the present study, this account predicts that both informative and uninformative (i.e., neutral) prestimulus cues will benefit memory performance compared to a no cue condition. This is the pattern of findings we observed with the source memory measure here. We argue that these results converge with those from a recent report by deBettencourt and colleagues (2021). Participants in this study studied sets of 4 images displayed at a specific (circular) location on a screen in a working memory task. Some trials contained prestimulus encoding cues that directed participants to covertly attend to the spatial location of one of the objects that was likely to be probed. Other trials contained neutral prestimulus encoding cues with all 4 locations cued. These conditions roughly correspond to our informative and uninformative cued conditions, respectively. Participants' working memory and long-term memory for the location of the objects were tested with a continuous report task (cf. Brady et al., 2013; Harlow & Donaldson, 2013). The results revealed that prestimulus cues during a working memory task were associated with more precise recollection of a stimulus-specific feature (e.g., location). Of interest to the present work, deBettencourt and colleagues (2021) found that prestimulus spatial cues also enhanced sustained attention (working memory performance over time) which was positively associated with the precision of recollecting stimuli features (e.g., location). Applying these findings to the present work, we speculate that informative and uninformative prestimulus cues may have affected sustained attention mechanisms during encoding (also see deBettencourt et al., 2018). For instance, both prestimulus cues may have increased sustained attention by reducing the likelihood of attentional lapses occurring during encoding, which benefited subsequent source memory performance (and potentially familiarity, as discussed above). Additionally, if prestimulus cues modulated more task specific opposed to sustained attentional processes, then we might have been more likely to observe increased source memory performance for informative prestimulus cues compared to uninformative and no prestimulus cues (as predicted by the task set hypothesis). Future studies are needed to examine how

prestimulus cues modulate different attentional processes and how their relationship contributes to subsequent memory effects.

It is unclear why the effects on recollection were only observed on the source memory measure and not on estimates of recollection derived from the dual process signal detection model. This was surprising, as these two measures are thought to capture the same underlying mnemonic process (Yonelinas, 1999). Consistent with supposition, recollection estimates derived from the dual process signal detection model were more strongly predictive of source memory than were familiarity estimates in the present experiments (see Supplemental Materials). Second, this lack of a concurrent effect on both indices of recollection was surprising given that prior neuroimaging work has observed prestimulus subsequent memory effects using both objective (Addante et al., 2015; de Chastelaine & Rugg, 2015; Ezzyat et al., 2017; Galli et al., 2012; Koen, Horne, et al., 2018; Liu et al., 2021) and subjective (Galli et al., 2012, 2013; Otten et al., 2006, 2010; Park & Rugg, 2010) recollection tasks. One way to reconcile the present findings with prior research is to argue that the subjective measures of recollection in previous EEG and fMRI research relied primarily on retrieval of criterial source details, such as stimulus modality (e.g., auditory versus visual) or semantic judgments (e.g., deep versus shallow), that were included in those studies. Additional research will be needed to identify if prestimulus cues differentially affect objective and subjective measures of recollection, and if so under what conditions. Importantly, if our finding that prestimulus cues at encoding benefit objective, but not subjective, measures of recollection hold, then this provides an important constraint on theories of prestimulus subsequent memory effects.

There are a couple possibilities for why we observed differences between our source memory and subjective recollection estimate. First, ‘non-criterial’ recollection’ may have contributed to the diverging pattern of results for subjective and objective measures of recollection (Parks, 2007; Toth & Parks, 2006; Yonelinas & Jacoby, 1996). That is, participants’ high confidence old/new judgments may have been supported by recollection of additional details (e.g., a random thought that came to mind when seeing the word) that provided no diagnostic information about which semantic task they performed on the word during the study phase. If true, then the informative and uninformative cues simply provided a shift in the relative proportion of recollection events that comprised the detail about the encoding task that was captured by the source memory measure, but not the dual-process estimate of recollection. A second possibility is that the null effect on subjective measures of recollection resulted from mismodelling of the receiver operator characteristic curves (for a discussion of this issue, see Jang et al., 2012; Klauer & Kellen, 2015; Koen et al., 2013; Koen & Yonelinas, 2010, 2013; Spanton & Berry, 2020; Starns et al., 2012; for reviews of signal detection models of memory, see Wixted, 2007; Yonelinas & Parks, 2007). For instance, the results might be different if recollection were modeled in a more continuous manner (e.g., deBettencourt et al., 2021; Harlow & Donaldson, 2013; Onyper et al., 2010). However, it is unclear how the criterial source memory detail in the present study would be best modeled in a continuous manner.

The discussion and conclusions drawn from the data thus far rests on the assumption that the dual-process model is the best characterization of recognition memory. However, there has been substantial debate as to whether a single-process or dual-process signal detection model provides a better account of recognition memory (e.g., Jang et al., 2012; Klauer & Kellen, 2015; Koen et al., 2013; Koen & Yonelinas, 2010, 2013; Spanton & Berry, 2020; Starns et al., 2012; for reviews of signal detection models of memory, see Wixted, 2007; Yonelinas & Parks, 2007). It is, therefore, necessary to consider if a single-process account might provide a better explanation of our findings. We believe it possible that a single-process model can readily accommodate the present data, particularly the graded increase in overall recognition memory performance. A single-process model, however, does not easily account for the non-graded effect of prestimulus cues on subsequent source memory performance. One way to reconcile the findings with a single-process model is to argue source memory effects were quite small overall, and thus might be too small to have a meaningful impact on overall recognition memory. Importantly, regardless of whether one adopts a single-process or dual-process interpretation of the present, the primary conclusion that prestimulus cues enhanced overall subsequent recognition memory performance in a graded manner is unchanged.

Critically, the present study does not distinguish between single-process and dual-process models of memory because it was not designed to do so. Neither theoretical account, to our knowledge, makes predictions about how different prestimulus cues will influence subsequent memory. Our choice to adopt the dual-process signal detection model (Yonelinas, 1994, 1999) as a measurement model was driven by findings from the neuroimaging literature linking prestimulus subsequent memory effects to recollection (e.g., Otten et al., 2006, 2010; Park & Rugg, 2010). As discussed previously, the conclusions associating prestimulus subsequent memory effects to recollection were derived from contrasts thought to isolate recollection related neural activity, such as associative and source memory tasks (Addante et al., 2015; Koen, Horne, et al., 2018; Liu et al., 2021) and subjective reports of recollection (de Chastelaine & Rugg, 2015; Otten et al., 2006, 2010; Park & Rugg, 2010). Another factor that contributed to our decision to adopt the dual-process signal detection model is a set of findings demonstrating that the parameters in this model behave in theoretically meaningful way whereas the parameters of the unequal-variance signal detection model, the most prominent single-process signal detection model, do not (Koen et al., 2013; Koen & Yonelinas, 2010, 2011; also see Yonelinas, 1999, 2001).

There are several other limitations about the present study. First, we did not directly compare the effects of cues on source memory and familiarity estimates. These measures are on different scales that require different assumptions, which precludes a direct comparison of the measures. Thus, any discussion of differences between mnemonic processes should be taken with caution as we do not demonstrate an interaction between mnemonic process and prestimulus cue type. Second the source memory detail in the current task was either inherently contained within the prestimulus cue (informative cue trials) or not (uninformative and no cue trials). Thus, it is unclear if prestimulus cues may benefit other source memory details beyond a

semantic judgment that was required to successfully complete the encoding task. One potentially interesting future direction is to examine whether prestimulus cues differentially influence source details that are not required for the encoding task, such as the location or color of the word on the screen.

Third, one could argue that the effects of prestimulus cues on subsequent memory performance were overall quite low (small to medium). The effect sizes observed here might be low due to additional noise caused by collecting most of the data through online means. Alternatively, we may have underestimated the prestimulus cue effect on memory performance because our no cue condition still contained some information that the participants may have found beneficial for encoding. The absence of an explicit cue in the no cue condition could have also served as a prestimulus cue due to the passage of time. Specifically, the longer a trial went on without a cue, the more likely the next trial would be a no cue trial. Participants may have picked up on this aspect of the design and used this information as another form of an uninformative prestimulus cue.

Lastly, there are many other factors that might systematically influence the extent to which prestimulus encoding cues affect subsequent memory performance. One factor, which varied across our four experiments, is whether the cue types are presented in an intermixed in a single list or blocked across multiple lists. It is possible that presentation that intermixed versus blocked presentation of the three prestimulus cue types influenced our results. For instance, intermixing the prestimulus cue types increases task difficulty which, in turn, might minimize the benefits of prestimulus cues on subsequent memory (Galli et al., 2013). However, the present experiments varied across numerous factors, including the participant recruitment pool used, in-person vs. online experiment format, the memory measures collected, prestimulus cue conditions included, and other design differences (e.g., timing) that existed across experiments precludes a systematic comparison of such issues in the present data. These design decisions are a limitation of the present investigation, and future research is needed to systematically examine how intermixed and blocked lists, as well as other variables (e.g., short vs. long cue-stimulus-intervals, short vs. long delayed test), influence how prestimulus encoding cues affect subsequent memory performance.

The present work suggests that prestimulus encoding cues affect multiple encoding processes that are differentially associated with subsequent recollection and familiarity. The informativeness of prestimulus encoding cues increased familiarity in a graded manner. Additionally, relative to no prestimulus cues, both informative and uninformative prestimulus cues enhanced source memory performance while leaving estimates of recollection unaffected. Future research is needed to expand upon these findings to examine if prestimulus cues affect other types of memory (e.g., priming, Düzel et al., 2005). Furthermore, future work using electrophysiological and neuroimaging techniques may uncover multiple processes that contribute to the influence of prestimulus cues on memory encoding through a systematic

comparison of different types of cues with contrast that can better isolate recollection and familiarity.

Acknowledgements

The results reported here were presented at the 2020 Psychonomic Society Virtual Meeting. We would like to thank Dr. Jessica D. Payne, Dr. Michael D. Rugg, Morgan Munsen, and Rachelle Pichot for providing comments on a previous version of this manuscript. The authors report no conflict of interest.

Joshua D. Koen was supported by grant R56AG068149 from the National Institute on Aging during the preparation of this manuscript. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

References

- Adcock, R. A., Thangavel, A., Whitfield-Gabrieli, S., Knutson, B., & Gabrieli, J. D. E. (2006). Reward-Motivated Learning: Mesolimbic Activation Precedes Memory Formation. *Neuron*, 50(3), 507–517. <https://doi.org/10.1016/j.neuron.2006.03.036>
- Addante, R. J., de Chastelaine, M., & Rugg, M. D. (2015). Pre-stimulus neural activity predicts successful encoding of inter-item associations. *NeuroImage*, 105, 21–31. <https://doi.org/10.1016/j.neuroimage.2014.10.046>
- Bollinger, J., Rubens, M. T., Zanto, T. P., & Gazzaley, A. (2010). Expectation-Driven Changes in Cortical Functional Connectivity Influence Working Memory and Long-Term Memory Performance. *Journal of Neuroscience*, 30(43), 14399–14410. <https://doi.org/10.1523/jneurosci.1547-10.2010>
- 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. <https://doi.org/10.1177/0956797612465439>
- Cohen, J. D. (1988). *Statistical power analysis for the social sciences* (2nd ed., Vol. 2nd). Lawrence Erlbaum.
- Cohen, N., Pell, L., Edelson, M. G., Ben-Yakov, A., Pine, A., & Dudai, Y. (2015). Peri-encoding predictors of memory encoding and consolidation. *Neuroscience & Biobehavioral Reviews*, 50, 128–142. <https://doi.org/10.1016/j.neubiorev.2014.11.002>
- de Chastelaine, M., & Rugg, M. D. (2015). The effects of study task on prestimulus subsequent memory effects in the hippocampus: Pre-Stimulus Activity and Depth of Encoding. *Hippocampus*, 25(11), 1217–1223. <https://doi.org/10.1002/hipo.22489>
- deBettencourt, M. T., Norman, K. A., & Turk-Browne, N. B. (2018). Forgetting from lapses of sustained attention. *Psychonomic Bulletin & Review*, 25(2), 605–611. <https://doi.org/10.3758/s13423-017-1309-5>
- deBettencourt, M. T., Williams, S. D., Vogel, E. K., & Awh, E. (2021). Sustained Attention and Spatial Attention Distinctly Influence Long-term Memory Encoding. *Journal of Cognitive Neuroscience*, 33(10), 2132–2148. <https://doi.org/10/gnkc7k>
- Diana, R. A., Yonelinas, A. P., & Ranganath, C. (2007). Imaging recollection and familiarity in the medial temporal lobe: A three-component model. *Trends in Cognitive Sciences*, 11(9), 379–386. <https://doi.org/10.1016/j.tics.2007.08.001>
- Düzel, E., Richardson-Klavehn, A., Neufang, M., Schott, B. H., Scholz, M., & Heinze, H.-J. (2005). Early, partly anticipatory, neural oscillations during identification set the stage for priming. *NeuroImage*, 25(3), 690–700. <https://doi.org/10.1016/j.neuroimage.2004.11.038>

- Eichenbaum, H., Yonelinas, A. P., & Ranganath, C. (2007). The Medial Temporal Lobe and Recognition Memory. *Annual Review of Neuroscience*, 30(1), 123–152. <https://doi.org/10.1146/annurev.neuro.30.051606.094328>
- Ezzyat, Y., Kragel, J. E., Burke, J. F., Levy, D. F., Lyalenko, A., Wanda, P., O’Sullivan, L., Hurley, K. B., Busygin, S., Pedisich, I., Sperling, M. R., Worrell, G. A., Kucewicz, M. T., Davis, K. A., Lucas, T. H., Inman, C. S., Lega, B. C., Jobst, B. C., Sheth, S. A., ... Kahana, M. J. (2017). Direct Brain Stimulation Modulates Encoding States and Memory Performance in Humans. *Curr. Biol.*, 27(9), 1251–1258. <https://doi.org/10.1016/j.cub.2017.03.028>
- Fellner, M.-C., Bäuml, K.-H. T., & Hanslmayr, S. (2013). Brain oscillatory subsequent memory effects differ in power and long-range synchronization between semantic and survival processing. *NeuroImage*, 79, 361–370. <https://doi.org/10.1016/j.neuroimage.2013.04.121>
- Francis, G., & Thunell, E. (2021). Reversing Bonferroni. *Psychonomic Bulletin & Review*, 28(3), 788–794. <https://doi.org/10/gjf8b7>
- Galli, G., Choy, T. L., & Otten, L. J. (2012). Prestimulus brain activity predicts primacy in list learning. *Cognitive Neuroscience*, 3(3–4), 160–167. <https://doi.org/10.1080/17588928.2012.670105>
- Galli, G., Gebert, A. D., & Otten, L. J. (2013). Available processing resources influence encoding-related brain activity before an event. *Cortex*, 49(8), 2239–2248. <https://doi.org/10.1016/j.cortex.2012.10.011>
- Gruber, M. J., & Otten, L. J. (2010). Voluntary Control over Prestimulus Activity Related to Encoding. *Journal of Neuroscience*, 30(29), 9793–9800. <https://doi.org/10.1523/jneurosci.0915-10.2010>
- Guderian, S., Schott, B. H., Richardson-Klavehn, A., & Duzel, E. (2009). Medial temporal theta state before an event predicts episodic encoding success in humans. *Proceedings of the National Academy of Sciences*, 106(13), 5365–5370. <https://doi.org/10.1073/pnas.0900289106>
- Harlow, I. M., & Donaldson, D. I. (2013). Source accuracy data reveal the thresholded nature of human episodic memory. *Psychonomic Bulletin & Review*, 20(2), 318–325. <https://doi.org/10.3758/s13423-012-0340-9>
- Jang, Y., Mickes, L., & Wixted, J. T. (2012). Three tests and three corrections: Comment on Koen and Yonelinas (2010). *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 38(2), 513–523. <https://doi.org/10.1037/a0025880>
- Kafkas, A. (2021). Encoding-linked pupil response is modulated by expected and unexpected novelty: Implications for memory formation and neurotransmission. *Neurobiology of Learning and Memory*, 180, 107412. <https://doi.org/10/gkzm9h>

- Kafkas, A., & Montaldi, D. (2018). Expectation affects learning and modulates memory experience at retrieval. *Cognition*, 180, 123–134. <https://doi.org/10/gff8h5>
- Kim, H. (2011). Neural activity that predicts subsequent memory and forgetting: A meta-analysis of 74 fMRI studies. *NeuroImage*, 54(3), 2446–2461. <https://doi.org/10.1016/j.neuroimage.2010.09.045>
- Klauer, K. C., & Kellen, D. (2015). The flexibility of models of recognition memory: The case of confidence ratings. *J. Math. Psychol.*, 67, 8–25. <https://doi.org/10.1016/j.jmp.2015.05.002>
- Koen, J. D., Aly, M., Wang, W.-C., & Yonelinas, A. P. (2013). Examining the causes of memory strength variability: Recollection, attention failure, or encoding variability? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 39(6), 1726–1741. <https://doi.org/10.1037/a0033671>
- Koen, J. D., Barrett, F. S., Harlow, I. M., & Yonelinas, A. P. (2017). The ROC Toolbox: A toolbox for analyzing receiver-operating characteristics derived from confidence ratings. *Behavior Research Methods*, 49(4), 1399–1406. <https://doi.org/10.3758/s13428-016-0796-z>
- Koen, J. D., Horne, E. D., Hauck, N., & Rugg, M. D. (2018). Age-related differences in prestimulus subsequent memory effects assessed with event-related potentials. *Journal of Cognitive Neuroscience*, 30(6), 829–850. https://doi.org/10.1162/jocn_a_01249
- Koen, J. D., Thakral, P. P., & Rugg, M. D. (2018). Transcranial magnetic stimulation of the left angular gyrus during encoding does not impair associative memory performance. *Cognitive Neuroscience*, 9(3–4), 127–138. <https://doi.org/10.1080/17588928.2018.1484723>
- Koen, J. D., & Yonelinas, A. P. (2010). Memory variability is due to the contribution of recollection and familiarity, not to encoding variability. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 36(6), 1536–1542. <https://doi.org/10.1037/a0020448>
- Koen, J. D., & Yonelinas, A. P. (2011). From humans to rats and back again: Bridging the divide between human and animal studies of recognition memory with receiver operating characteristics. *Learning & Memory*, 18(8), 519–522. <https://doi.org/10.1101/lm.2214511>
- Koen, J. D., & Yonelinas, A. P. (2013). Still no evidence for the encoding variability hypothesis: A reply to Jang, Mickes, and Wixted (2012) and Starns, Rotello, and Ratcliff (2012). *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 39(1), 304–312. <https://doi.org/10.1037/a0028462>
- Lenth, R. V. (2021). *emmeans: Estimated marginal means, aka least-squares means* [Manual]. <https://CRAN.R-project.org/package=emmeans>
- Lin, H., Xiang, J., Li, S., Liang, J., & Jin, H. (2015). Anticipation of Negative Pictures Enhances the P2 and P3 in Their Later Recognition. *Frontiers in Human Neuroscience*, 9. <https://www.frontiersin.org/article/10.3389/fnhum.2015.00646>

- Lin, H., Xiang, J., Li, S., Liang, J., Zhao, D., Yin, D., & Jin, H. (2017). Cued uncertainty modulates later recognition of emotional pictures: An ERP study. *International Journal of Psychophysiology*, 116, 68–76. <https://doi.org/10.1016/j.ijpsycho.2017.03.004>
- Liu, E. S., Koen, J. D., & Rugg, M. D. (2021). Effects of age on prestimulus neural activity predictive of successful memory encoding: An fMRI study. *Cerebral Cortex*, 31(2), 917–932. <https://doi.org/10.1093/cercor/bhaa265>
- Mackiewicz, K. L., Sarinopoulos, I., Cleven, K. L., & Nitschke, J. B. (2006). The effect of anticipation and the specificity of sex differences for amygdala and hippocampus function in emotional memory. *Proceedings of the National Academy of Sciences*, 103(38), 14200–14205. <https://doi.org/10.1073/pnas.0601648103>
- Mattson, J. T., Wang, T. H., de Chastelaine, M., & Rugg, M. D. (2014). Effects of Age on Negative Subsequent Memory Effects Associated with the Encoding of Item and Item-Context Information. *Cerebral Cortex*, 24(12), 3322–3333. <https://doi.org/10.1093/cercor/bht193>
- Merkow, M. B., Burke, J. F., Stein, J. M., & Kahana, M. J. (2014). Prestimulus theta in the human hippocampus predicts subsequent recognition but not recall: Item Recognition Versus Free Recall. *Hippocampus*, 24(12), 1562–1569. <https://doi.org/10.1002/hipo.22335>
- Onyper, S. V., Zhang, Y. X., & Howard, M. W. (2010). Some-or-none recollection: Evidence from item and source memory. *J. Exp. Psychol. Gen.*, 139(2), 341–364. <https://doi.org/10.1037/a0018926>
- Otten, L. J., Quayle, A. H., Akram, S., Ditlew, T. A., & Rugg, M. D. (2006). Brain activity before an event predicts later recollection. *Nature Neuroscience*, 9(4), 489–491. <https://doi.org/10.1038/nn1663>
- Otten, L. J., Quayle, A. H., & Puvaneswaran, B. (2010). Prestimulus Subsequent Memory Effects for Auditory and Visual Events. *Journal of Cognitive Neuroscience*, 22(6), 1212–1223. <https://doi.org/10.1162/jocn.2009.21298>
- Park, H., & Rugg, M. D. (2010). Prestimulus hippocampal activity predicts later recollection. *Hippocampus*, 20, 24–28. <https://doi.org/10.1002/hipo.20663>
- Parks, C. M. (2007). The role of noncriterial recollection in estimating recollection and familiarity. *Journal of Memory and Language*, 57(1), 81–100. <https://doi.org/10.1016/j.jml.2007.03.003>
- Peer, E., Vosgerau, J., & Acquisti, A. (2014). Reputation as a sufficient condition for data quality on Amazon Mechanical Turk. *Behavior Research Methods*, 46(4), 1023–1031. <https://doi.org/10.3758/s13428-013-0434-y>
- Peirce, J. W. (2007). PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods*, 162(1–2), 8–13. <https://doi.org/10.1016/j.jneumeth.2006.11.017>

- Peirce, J. W., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, 51(1), 195–203. <https://doi.org/10.3758/s13428-018-01193-y>
- Salari, N., & Rose, M. (2016). Dissociation of the functional relevance of different pre-stimulus oscillatory activity for memory formation. *NeuroImage*, 125, 1013–1021. <https://doi.org/10.1016/j.neuroimage.2015.10.037>
- Singmann, H., Bolker, B., Westfall, J., Aust, F., & Ben-Shachar, M. S. (2021). *afex: Analysis of factorial experiments* [Manual]. <https://CRAN.R-project.org/package=afex>
- Snodgrass, J. G., & Corwin, J. (1988). Pragmatics of Measuring Recognition Memory: Applications to Dementia and Amnesia. *Journal of Experimental Psychology: General*, 117(1), 34–50. <https://doi.org/10.1037/0096-3445.117.1.34>
- Spanton, R. W., & Berry, C. J. (2020). The unequal variance signal-detection model of recognition memory: Investigating the encoding variability hypothesis. *Quarterly Journal of Experimental Psychology*, 73(8), 1242–1260. <https://doi.org/10.1177/1747021820906117>
- Starns, J. J., Rotello, C. M., & Ratcliff, R. (2012). Mixing strong and weak targets provides no evidence against the unequal-variance explanation of zROC slope: A comment on Koen and Yonelinas (2010). *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 38(3), 793–801. <https://doi.org/10.1037/a0027040>
- Toth, J. P., & Parks, C. M. (2006). Effects of age on estimated familiarity in the process dissociation procedure: The role of noncriterial recollection. *Memory & Cognition*, 34(3), 527–537. <https://doi.org/10.3758/bf03193576>
- Tulving, E. (1984). Précis of Elements of episodic memory. *Behavioral and Brain Sciences*, 7(2), 223–238. <https://doi.org/10.1017/s0140525x0004440x>
- Uncapher, M. R., Hutchinson, J. B., & Wagner, A. D. (2011). Dissociable Effects of Top-Down and Bottom-Up Attention during Episodic Encoding. *Journal of Neuroscience*, 31(35), 12613–12628. <https://doi.org/10.1523/jneurosci.0152-11.2011>
- Wagner, A. D., Schacter, D. L., Rotte, M., Koutstaal, W., Maril, A., Dale, A. M., Rosen, B. R., & 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>
- Wixted, J. T. (2007). Dual-process theory and signal-detection theory of recognition memory. *Psychological Review*, 114(1), 152–176. <https://doi.org/10.1037/0033-295x.114.1.152>
- Yonelinas, A. P. (1994). Receiver-Operating Characteristics in Recognition Memory: Evidence for a Dual-Process Model. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 20(6), 1341–1354. <https://doi.org/10.1037/0278-7393.20.6.1341>

- Yonelinas, A. P. (1999). The Contribution of Recollection and Familiarity to Recognition and Source-Memory Judgments: A Formal Dual-Process Model and an Analysis of Receiver Operating Characteristics. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 25(6), 1415–1434. <https://doi.org/10.1037/0278-7393.25.6.1415>
- Yonelinas, A. P. (2001). Consciousness, control, and confidence: The 3 Cs of recognition memory. *Journal of Experimental Psychology: General*, 130(3), 361–379. <https://doi.org/10.1037//0096-3445.130.3.361>
- Yonelinas, A. P., Aly, M., Wang, W.-C., & Koen, J. D. (2010). Recollection and familiarity: Examining controversial assumptions and new directions. *Hippocampus*, 20(11), 1178–1194. <https://doi.org/10.1002/hipo.20864>
- Yonelinas, A. P., & Jacoby, L. L. (1996). Noncriterial Recollection: Familiarity as Automatic, Irrelevant Recollection. *Consciousness and Cognition*, 5(1–2), 131–141. <https://doi.org/10.1006/ccog.1996.0008>
- Yonelinas, A. P., & Parks, C. M. (2007). Receiver operating characteristics (ROCs) in recognition memory: A review. *Psychological Bulletin*, 133(5), 800–832. <https://doi.org/10.1037/0033-2909.133.5.800>