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Title
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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 48(0)

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Publication Date
2026

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Selective Effects of Task Change-Driven Event Boundaries on Recognition Memory

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Abstract

How do different forms of contextual change segment ongoing experience into discrete events? How do such boundaries influence memory for information encountered around them? While event boundaries are known to affect recognition memory, their impact on fine-grained mnemonic discrimination remains largely unexplored. Prior work (Morse et al., 2023) reported boundary-related memory effects when multiple sources of contextual change co-occurred, leaving open which type of change is critical. Building on this work, we used a design that separates two sources of contextual change that were previously confounded: shifts in stimulus domain and shifts in task context. We contrasted these by introducing stimulus-domain shifts (image category changes; Experiment 1) and task-context shifts (changes in the encoding judgment; Experiment 2). Following encoding, participants completed recognition and lure discrimination tests. Reliable boundary effects emerged only for task-context shifts, which produced a post-boundary decline in recognition accuracy. Stimulus-domain shifts did not yield comparable effects, and neither manipulation influenced lure discrimination. These findings indicate that shifts in task context alone are sufficient to induce boundary-related memory effects, highlighting a central role for changes in goals and attentional set in event segmentation.

Keywords: event segmentation; recognition memory; pattern separation; mnemonic discrimination

Introduction

We organize our continuous stream of experience into meaningful chunks or events (Zacks & Swallow, 2007). This process, known as event segmentation, structures ongoing experience by parsing it into segments separated by event boundaries (DuBrow et al., 2024; Zacks et al., 2007). These boundaries are salient moments and serve as anchor points, influencing how information is organized and later retrieved (Yates et al., 2023; Zacks & Swallow, 2007). A large body of work demonstrates that event boundaries shape multiple expressions of memory, including temporal order memory (DuBrow & Davachi, 2013; Heusser et al., 2018; Wen & Egner, 2022), subjective duration judgments (Lositsky et al., 2016; Sherman et al., 2023; Wen & Egner, 2022), associative memory (item-context binding) (Heusser et al., 2018; Siefke et al., 2019; Su et al., 2025), and recognition memory (Morse et al., 2023; Swallow et al., 2009; Zheng et al., 2022). Together, these findings establish event segmentation as a fundamental mechanism through which experience is organized in memory.

Event boundaries can be triggered by multiple forms of contextual change that differ in the source driving segmentation. One type involves stimulus-domain shifts, such as changes in visual scenes, image categories, or sensory features, which reflect shifts in perceptual input and drive memory effects (Clewett et al., 2020; Heusser et al., 2018; Sherman et al., 2023). Another involves task-context shifts, where externally or internally driven changes in goals or task demands drive segmentation (DuBrow & Davachi, 2013; Morse et al., 2023; Wang & Egner, 2022). Emotional shifts can also shape event structure (R. Chen & Swallow, 2025; McClay et al., 2023). Critically, these forms of contextual change may not be equivalent and may engage distinct cognitive mechanisms during encoding. This raises a key question for understanding event segmentation and memory: do different types of contextual change differentially drive event segmentation and its impact on memory?

To address the above question, we directly compare stimulus-domain shifts (changes in image category) and task-context shifts (changes in encoding task). Specifically, we examine how these changes influence two key aspects of memory, recognition memory and pattern separation, which remain underexplored in the event segmentation literature.

Evidence for boundary-related memory effects following contextual changes is mixed. For example, Wang and Egner (2022) showed that task-goal changes, while keeping image categories constant, produce reliable event boundaries reflected in disrupted temporal order memory and distance judgments. In contrast, using a similar task-context manipulation, Morse et al. (2023) did not observe corresponding effects on recognition memory, instead finding that combined perceptual and task shifts were necessary to produce segmentation and memory effects. These differences may reflect the distinct memory measures used or subtle variations in experimental design. Meanwhile, although stimulus-domain shifts (e.g., item-category changes) have been studied in complex video stimuli (Flores et al., 2017; Swallow et al., 2009), their effects on recognition memory remain underexplored (Morse et al., 2023). Together, these findings highlight the need for a more systematic comparison across boundary types and memory measures. Our predictions regarding recognition memory consequences are informed by theoretical and neural evidence from the existing literature.

Event Segmentation Theory (EST; Zacks et al., 2007) provides a framework for understanding how event boundaries influence memory. According to EST, boundaries are trig-

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gered by increases in prediction error, prompting updates to an internal event model that tracks ongoing experience. This updating process may reallocate cognitive resources toward constructing or retrieving a new event model, transiently disrupting encoding of incoming information (Pradhan & Kumar, 2022; Zacks et al., 2007). Event boundaries may also trigger rapid reinstatement of recently encoded information (Sols et al., 2017), biasing processing toward retrieval-like states and reducing resources available for encoding new items (Long & Kuhl, 2019). Consequently, items encountered immediately after a boundary may be encoded less effectively. Based on this framework, we hypothesized that recognition memory will be impaired for post-boundary items relative to mid-event and pre-boundary items.

Neurally, event boundaries have been linked to hippocampal activity associated with memory encoding and retrieval (e.g., Baldassano et al., 2017; Barnett et al., 2024; Ben-Yakov and Henson, 2018). These effects may extend across hippocampal subfields supporting distinct memory computations (Collin, 2025) and may facilitate integration of preceding information into coherent event representations (Mishra et al., 2025). Given the role of hippocampal subfields such as the dentate gyrus and CA3 in pattern separation, i.e., distinguishing highly similar experiences, event boundaries may also influence fine-grained memory discrimination measured through lure discrimination tasks (Stark et al., 2013, 2019). Accordingly, we examined whether lure discrimination is modulated by event boundaries induced by task changes or item-category changes. Importantly, the present study relies on behavioral measures, and links to underlying neural mechanisms remain speculative.

In summary, we conducted two experiments in which event boundaries were instantiated as image category shifts and task-context shifts. We compared recognition and lure discrimination performance at pre-boundary, post-boundary, and mid-event positions. We found that task-context change, but not item-category change, produced reliable behavioral markers of segmentation, as reflected in the increased response times (RTs) following boundaries. Critically, task-context shifts were associated with impaired recognition memory for post-boundary items, whereas no corresponding effects were observed for lure discrimination. We discuss these findings in relation to theoretical accounts of event segmentation and post-boundary processing.

Materials and methods

We based our design on that of Morse et al. (2023), who examined pre- and post-boundary recognition memory and pattern separation. Memory was assessed using the Mnemonic Similarity Task (MST; Stark et al. 2019). During encoding, participants viewed objects or scenes with an encoding question(s). At test, stimuli included targets (the images presented during the encoding phase), lures (visually and conceptually similar to targets), and foils (novel items), and participants provided an "old/new" response to each stimulus.

Morse et al. (2023) structured MST trials as events and conducted three experiments with event boundaries putatively induced by stimulus category change, task-context shift, or both simultaneously. Boundary effects emerged only when both manipulations were present, with reduced recognition memory immediately after boundaries and enhanced lure discrimination immediately before boundaries. We replicated the stimulus category change and task context shift experiments. Stimulus category shifts were implemented by switching between objects and scenes and task context shifts by changing the encoding question ("Indoor or Outdoor?" vs. "Manmade or Natural?").

We also addressed several limitations of the original design. First, the original study used a two-choice old/new test, which conflates lure rejection due to fine-grained discrimination (i.e., rejecting a similar lure based on precise memory) with forgetting (i.e., rejecting it due to imprecise memory). We instead used the standard three-choice MST response format (old/similar/new). The "similar" response is important, as the old/new binary choice can lead to participants adopting a conservative criterion ("only say old if it is identical") and achieving a high "LDI" (defined in their work as $LDI = p(\text{“new”} \mid \text{Lure}) - p(\text{“old”} \mid \text{Foil})$). Second, task context-change boundaries may have been weakened by semantic overlap between encoding questions (e.g., natural items are more likely to be outdoors). We therefore replaced "Manmade or Natural?" with "Does it fit in a shoebox?" to remove this correlation. Third, some scene images resembled isolated objects against neutral backgrounds, increasing cross-category similarity; these images were excluded. Fourth, MST stimuli vary systematically in target–lure similarity (lure bins 1–5), which provides a sensitive measure of mnemonic discrimination (Stark et al., 2013). Because lure-bin distributions were uncontrolled in Morse et al. (2023), uneven sampling of target-lure similarities might have confounded temporal position effects. We ensured equal lure-bin representation across conditions. While object stimuli were already assigned to lure bins (Stark et al., 2019), scene stimuli lacked such assignments; therefore, we used *DreamSim*[1] model-derived cosine distances (Fu et al., 2023) and the object-set similarity distributions as a reference to assign scene (target-lure) pairs to comparable similarity bins.

With the inclusion of the "similar" response, we calculated the standard Lure Discrimination Index (LDI) as $LDI = p(\text{“similar”} \mid \text{Lure}) - p(\text{“similar”} \mid \text{Foil})$, which isolates fine-grained mnemonic discrimination, a hippocampal-dependent process known to decline with age (Yassa & Stark, 2011). Gist-level recognition was indexed by the recognition score (REC), $REC = p(\text{“old”} \mid \text{Target}) - p(\text{“old”} \mid \text{Foil})$.

Figure 1 summarizes the experimental design. All participants provided informed consent, and the protocol was approved by the IRB of the International Institute of Information Technology Hyderabad (IIIT-H).

[1] model available at https://github.com/ssundaram21/dreamsim

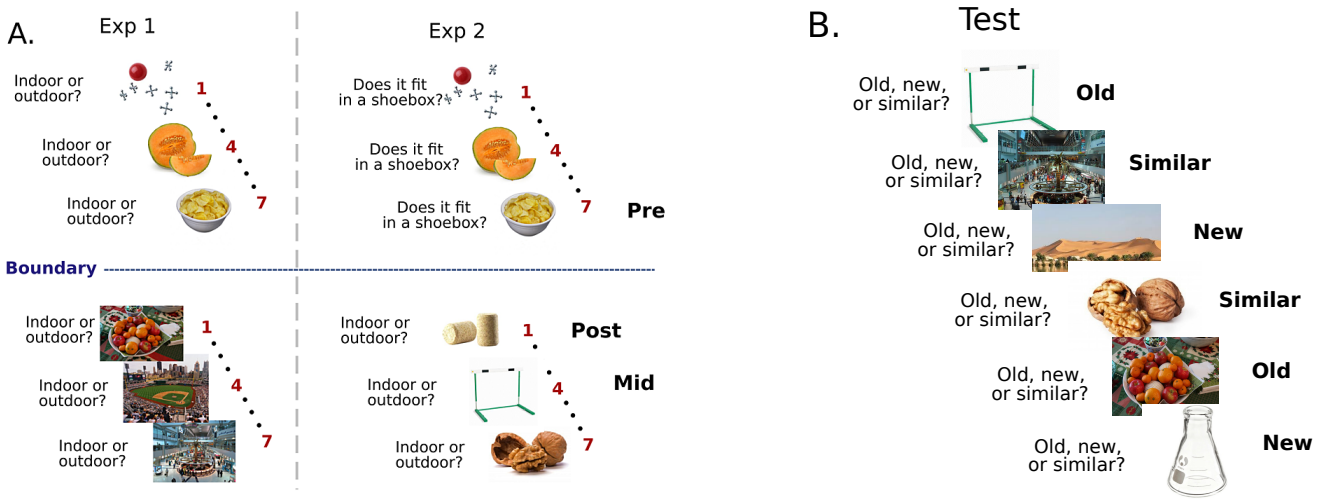

Figure 1: **Experimental design.** **(A)** Encoding phase. The task remained constant across the boundary in Exp 1, with only the image category changing ("item category"), whereas only the encoding task changed across the boundary in Exp 2 ("task context"). **(B)** Test phase, which is common for both experiments.

Experiment 1

In this experiment, we assessed recognition memory and lure discrimination accuracy for pre- and post-boundary items relative to mid-event items when event boundaries are instantiated only by a change in stimulus category.

Participants 55 participants (ages 19–35, M = 22.07, SD = 10.72; 18 females, 37 males) were recruited from a statistical methods course at IIIT-H and received course credit for their participation.

Stimuli Stimuli were drawn from object and scene image sets curated by Stark and colleagues for the Mnemonic Similarity Task (MST)[2]. Object images depicted common everyday items on white backgrounds, whereas scene images contained objects, people, or buildings embedded in meaningful contexts. We selected one of the six available object sets and used the single available scene set. Object foils were drawn from a different object set, and scene foils were sourced from the internet, ensuring no duplicates.

In both experiments, the tendency to endorse lures as "old" decreased with decreasing similarity to the targets ($F(4, 745) = 34, p < 0.0001$), indicating that the similarity manipulation worked as expected.

Procedure The experiment was implemented in PsychoPy. Participants first completed a 20-minute encoding phase in which they viewed 280 (140 objects, 140 scenes) randomly selected from the stimulus sets. Images were organized into 40 events of 7 images each. Each image was presented with the encoding question, "Indoor (F) or Outdoor (J)?", and participants responded using the F or J keys. Images remained onscreen for 3 seconds; if no response was made within this interval, the question remained onscreen until a response was registered, followed by a 0.5-second fixation ISI. Event boundaries were instantiated by changes in image category (objects to scenes or vice versa). We focused on three critical positions within each event: the pre-boundary item (final item before the category change), the post-boundary item (first item after the change), and the mid-event item (fourth item in the event).

To ensure participants registered item-category changes, instructions explicitly defined what constituted an "object" versus a "scene." Participants completed a brief practice session and were instructed not to look at the keyboard while responding. Attention was assessed using a predetermined annotated subset of approximately 100 object and scene trials for which a correct response was expected (e.g., a beach scene should be categorized as outdoor (J)). Participants scoring below 80% on these vigilance-check trials were excluded from further analysis; but all 55 participants passed.

After a 5-minute break, participants completed a self-paced test phase. They were instructed on the three response categories: "similar" (conceptually the same and visually very similar to the encoded image), "old" (the exact same image), and "new" (an entirely different image). Participants were shown two example lure images illustrating the distinction between "similar" and "old" responses. Participants pressed 'O' for old, 'S' for similar, and 'N' for new responses. The test phase included 150 test images: 60 targets, 60 lures, and 30 foils, with 20 target and 20 lure items each drawn from the mid-event, pre-boundary, and post-boundary positions. RTs were recorded during both the encoding and test phases.

Analysis We followed the analytical approach of Morse et al. (2023). First, we tested whether encoding-question RT differed across pre-, mid-, and post-boundary items. Post-boundary RT slowing reflects updating of event structure (Heusser et al., 2018); thus, slower RTs indicate successful

[2]stimuli available at https://github.com/celstark/MST

establishment of event boundaries by the contextual change manipulation. Because Q-Q plots revealed deviations from normality, violating ANOVA assumptions, we used a linear mixed-effects model with RT as the dependent variable, stimulus position (pre, mid, post) as the fixed effect, and participants as random intercepts. Unlike Morse et al. (2023), we did not include stimulus type (target or lure) as a factor because encoding RT cannot be influenced by whether an item later appeared as a target or lure during the test phase.

To quantify participants' ability to correctly recognize images encountered during encoding, we computed REC and LDI scores for each participant at each item position. We assume event boundaries modulate memory performance on images in the vicinity of the boundary and therefore consider performance on mid-event images as a within-subject "baseline". We then conducted both frequentist and Bayesian one-sample t-tests on the baseline-corrected pre-boundary and post-boundary LDI and REC scores to examine the effect of event boundaries on recognition memory and lure discrimination.

Beyond replicating the analyses of Morse et al. (2023), we conducted additional trial-level analyses using generalized linear mixed-effects models (*glmer*) in *R*. Separate models were fit for lure and target trials, with lure or target accuracy (0/1) as the binary dependent variable, stimulus position (pre-boundary, post-boundary, or mid-event) as the fixed effect, and participants included as random intercepts. Model assumptions were evaluated using the *DHARMa* package in *R*. To complement these analyses, we also fit Bayesian mixed-effects models using the *BRMS* package in *R*.

Experiment 2

In this experiment, we assessed recognition memory and lure discrimination accuracy for pre- and post-boundary items relative to mid-event items when event boundaries are instantiated by encoding task context changes alone.

Participants 50 participants (ages 19–39, M = 22.53, SD = 9.56; 10 females, 40 males) were recruited from a statistical methods course at IIIT-H and received course credit for participation. As in Experiment 1, participants scoring below 80% in the encoding task were excluded. Accordingly, one participant was excluded for scoring below the vigilance check threshold, and another was excluded due to an unregistered vigilance score caused by a system failure.

Stimuli The stimuli used in this experiment were the same as those employed in Experiment 1. However, in this experiment, only objects were used to maintain a consistent stimulus category across task context-driven event boundaries.

Procedure In Experiment 2, event boundaries were instantiated by a change in only the encoding task, i.e., "Indoor (F) or Outdoor (J)?" to "Does it fit in a shoebox? Yes (F) or No (J)" and vice versa. The image category remained constant throughout the course of the experiment.

To validate our assumption that encoding-task changes introduced smaller perceptual differences than item-category changes, we quantified visual similarity across event boundaries in both experiments by extracting screenshots immediately before and after each boundary and computing cosine distances between DINOv2 image embeddings (Oquab et al., 2023). Item-category shifts (Experiment 1) produced significantly larger across-boundary distances than task-context shifts (Experiment 2) ($t(998) = 27.06, p < .001$), suggesting that differences between the experiments cannot be attributed to perceptual changes introduced by the encoding-question text in Experiment 2. All other procedural details were identical across experiments.

Analysis All analyses were identical to those in Experiment 1. Additionally, we fit a generalized linear mixed-effects model with accuracy as the dependent variable, experiment (1 vs. 2), position (pre, mid, post), and their interaction as fixed effects, and participants as random intercepts, to directly test whether position effects differed across experiments. To examine encoding-task RT differences across experiments as a function of position, we also fit a linear mixed-effects model (LMM) with the same fixed and random effects. In both models, the post-boundary position served as the baseline level, so the observed main effects were all w.r.t. the post-boundary performance.

Results

Experiment 1: Image category change

The linear mixed-effects model did not reveal any significant difference in RT (Table 1) of the post-boundary encoding question compared to the mid position ($\beta = 0.038, SE = 0.029, z = 1.339, p = 0.181$) and the pre-boundary positions ($\beta = 0.046, SE = 0.029, z = 1.616, p = 0.106$), indicating that the change in stimulus category did not produce reliable boundary effects.

A one-sample t-test revealed that LDI and REC scores are all significantly above chance level ($p < 0.0001$). There was no significant difference between any of the scores (both REC and LDI) of mid-events, pre- and post-boundary items (all $p > 0.20$). To further assess these null results, we conducted Bayesian t-tests. Across all comparisons, Bayes Factors ($BF_{10} = 0.15 - 0.30$) indicated moderate evidence in favor of the null hypothesis, suggesting that performance at boundary positions (pre- and post-) did not reliably differ from mid-event (mid) positions. Figures 2 A & 2 B show the distribution of LDI and REC scores, respectively.

To explain trial-level performance as well as to account for participant-specific variability, we fitted a generalized mixed-effects model with random effects for participants. The model revealed the same pattern, with no pre- or post-boundary effects on lure discrimination or target accuracy compared to mid-event items (all $p > 0.4$). Both models pass all DHARMa diagnostic tests. A Bayesian mixed-effects logistic regression indicated no clear evidence for an

effect of position on accuracy, as the 95% credible intervals for both mid ($\beta = 0.02, 95\%CrI[-0.16, 0.21]$) and pre ($\beta = -0.06, 95\%CrI[-0.24, 0.12]$) included zero.

Table 1: Mean LDI (lure discrimination index) and REC (recognition memory index) scores and mean encoding task RT (response time) in seconds of experiments 1 and 2.

Experiment	Measure	pre	mid	post
Change in item category	LDI	0.31	0.33	0.31
	REC	0.63	0.64	0.63
	RT (s)	1.83	1.82	1.78
Change in encoding task	LDI	0.40	0.38	0.40
	REC	0.64	0.61	0.57
	RT (s)	2.17	2.19	2.44

In summary, these findings suggest that changes in stimulus category alone are insufficient to trigger event segmentation, as they produced neither behavioral boundary signatures (RT costs) nor effects on memory performance.

Experiment 2: Task change

Encoding task RT (Table 1) was significantly slower for post-boundary items compared to the mid- ($\beta = -0.254, SE = 0.034, z = -7.542, p < 0.0001$) and pre-boundary positions ($\beta = -0.269, SE = 0.034, z = -8.005, p < 0.0001$), indicating the occurrence of an event boundary. Additionally, a linear mixed-effects model including experiment and position (pre, mid, post) as fixed effects revealed a significant main effect of experiment, with slower RTs in Experiment 2 ($\beta = 0.35, SE = 0.12, t = 3.02, p = .003$). This effect was moderated by position, with a larger condition difference at the post position ($\beta = 0.31, SE = 0.04, t = 6.95, p < 0.0001$), once again indicating the establishment of an event boundary, which results in a slower RT, likely due to the updation of an event model.

Memory performance (LDI and REC scores) was significantly above chance level (one-sample t-test; $p < 0.0001$). Post-boundary REC performance tends to be lower than mid-event, although not statistically significant (one-sample t-test using corrected scores relative to mid-event performance; $t(49) = -1.759, p = 0.085$). Post-boundary REC is significantly worse than pre-boundary (paired-samples t-test; $t(49) = -2.738, p = 0.009$). There was no effect of position on LDI (all $p > 0.35$).

To further assess these effects and to evaluate evidence for null effects, we conducted analogous Bayesian statistical tests. Bayes factors indicated moderate evidence in favor of the null hypothesis for LDI and most position comparisons ($BF_{10} = 0.15 - 0.22$). In contrast, for REC, the pre- versus post-boundary comparison showed clear evidence for a decline in performance across the boundary ($BF_{10} = 4.28$), whereas the mid-event versus post-boundary comparison remained inconclusive ($BF_{10} \approx 0.64$). Figures 2 C & 2 D show the distribution of LDI and REC scores.

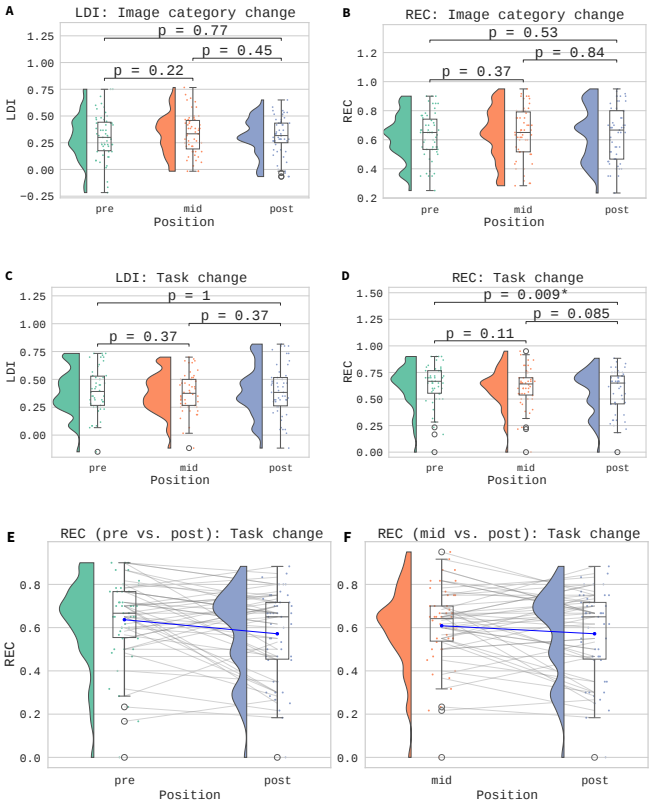

Figure 2: Effects of image category and task context changes on recognition (REC) and lure discrimination (LDI). (A) LDI and (B) REC for the image category change experiment. (C) LDI and (D) REC for the task-change experiment, REC was significantly reduced at post-boundary relative to pre-boundary trials (p = .009). (E–F) Within-subject comparisons of REC for (E) pre- vs. post- and (F) mid- vs. post-boundary trials in the task-change experiment: grey lines represent individual participants and the blue line indicates the mean trends.

To account for trial-level performance as well as participant-specific variability, we fitted a $GLMM$ with random effects for participants. The model revealed significantly worse post-boundary recognition memory compared to pre-boundary recognition memory ($\beta = -0.200, SE = 0.095, z = -2.100, p = 0.036$). There was no significant difference between post- and pre-boundary lure discrimination accuracy ($\beta = -0.078, SE = 0.093, z = 0.839, p = 0.401$) and post-boundary and mid-event lure discrimination accuracy ($\beta = -3.528 \times 10^{-6}, SE = 0.093, z = 0.00, p = 1.000$). Both models passed all DHARMa diagnostic tests.

A Bayesian mixed-effects logistic regression indicated evidence for higher trial-level recognition memory accuracy for pre-boundary compared to post-boundary items ($\beta = 0.32, 95\%CrI[0.13, 0.50]$). In contrast, there was no clear evidence for a difference between mid- and post-boundary positions, as the 95% credible interval included zero ($\beta = 0.18, 95\%CrI[-0.01, 0.36]$).

Finally, we ran $GLMM$ with recognition accuracy as the dependent variable, experiment and position (pre, mid, post)

as fixed effects and their interaction, and participant as a random intercept to assess whether any position-related effects differed as a function of experiment (i.e., type of event boundary). Only when using post-boundary scores as the baseline, we observe a significant effect of experiment ($\beta = -0.37, SE = 0.16, z = -2.212, p = .027$), implying that performance on post-boundary images decreases as we go from Experiment 1 to 2. A significant interaction between experiment and position revealed that post- to pre-boundary performance differed between Experiments 1 and 2 ($\beta = 0.37, SE = 0.136, z = 2.725, p = .006$) but mid- to post-boundary did not ($p = .26$). This pattern indicates that the overall difference between experiments was primarily driven by a selective increase in the pre–post boundary effect in Experiment 2.

Discussion

To examine how event boundaries instantiated by stimulus-domain and task-context changes affect recognition memory and lure discrimination, we replicated the second and third experiments of Morse et al. (2023) with a few modifications, as discussed in the Materials and methods section.

Unlike Morse et al. (2023), we observed a significant increase in the RT immediately following the change in task context (Experiment 2). This suggests that task changes and the goal shift they induce can trigger event boundaries (Wang et al., 2024). This also indicates that the task-change manipulation used in Morse et al. (2023) may not have been sufficiently disruptive to alter ongoing cognitive processing to update the event model. Broadly, this further underscores a more general methodological challenge: experimental designs must ensure that both the stimulus and the task effectively engage the intended mental processes (Pooja et al., 2024).

In Experiment 1, we did not observe an increase in RTs for post-boundary items, suggesting that the change in image category shifts (objects vs. scenes) was insufficient to induce event segmentation. In contrast, prior work has shown that perceptual changes, particularly accompanied by changes in task or context, can successfully trigger event segmentation (Heusser et al., 2018; Radvansky & Copeland, 2006). For instance, changes in background color—although superficially perceptual—disrupt a consistent object–context binding, thereby triggering an update in the event structure (Heusser et al., 2018; Xiang et al., 2025). In our study, however, although there was a stable object or scene context, the specific MST stimuli varied substantially across trials, and the task remained constant. Thus, unlike paradigms with persistent contextual cues such as stable background colors, category shifts alone may have been insufficient to induce event segmentation. Nevertheless, this interpretation remains speculative and requires further empirical validation.

Consistent with the absence of RT slowing at item-category boundaries, we found no effect of stimulus position on LDI or REC. In contrast, the task-change condition produced a significant boundary effect, with REC scores lower for post- than pre-boundary items. Switching to a new event model may momentarily engage retrieval-related processes, consistent with evidence that encoding and retrieval rely on competing neural states (Long & Kuhl, 2019). Indeed, increased RTs following task changes suggest the occurrence of event segmentation. Our findings also align with evidence that rapid neural reinstatement of the just-encoded event occurs after event boundaries (Sols et al., 2017), as such replay may interfere with encoding of post-boundary items.

Contrary to our prediction, boundaries did not affect LDI. In contrast, Morse et al. (2023) reported enhanced lure discrimination immediately before boundaries driven by combined perceptual and task changes. One possible explanation is that their two-choice (old/new) task could not distinguish between precise memory and forgetting, as both can produce a "new" response to a foil, potentially inflating LDI scores. Uneven target–foil similarity across boundary positions may also have contributed to their effects. Our null LDI result, obtained using design choices that address these limitations, is therefore likely meaningful. One possibility is that the experimental design did not elicit substantial prediction error because event changes occurred predictably every 7 items. Prediction errors, through "mismatch signals" (J. Chen et al., 2015; Y. Chen et al., 2024; Kumaran & Maguire, 2006), are thought to shift the hippocampus into an encoding-oriented state (Bein et al., 2020), which is associated with stronger pattern separation processes (Kesner, 2013; Lee & Kesner, 2004). In the absence of prediction error, the hippocampus may instead remain biased toward retrieval, reducing engagement of encoding-related processes such as pattern separation and thereby contributing to the null LDI effects.

Together, these findings suggest that not all contextual changes produce robust event boundaries or uniformly influence memory. Although boundaries following a task change impaired recognition memory, they did not affect lure discrimination ability. Future work should therefore use task designs that more effectively engage the intended memory processes, potentially through less predictable or more naturalistic event structures that elicit stronger prediction error signals. This is particularly important because lure discrimination performance provides a sensitive measure of age-related declines in mnemonic discrimination that may not be captured by overall recognition accuracy (Stark et al., 2013). Understanding whether and when event boundaries enhance these processes may therefore advance theoretical accounts of event cognition and memory and inform learning and memory-support interventions aimed at reducing interference and improving memory across the lifespan.

Acknowledgments

We acknowledge Aruneek Biswas and Mafruz Rahman for their valuable feedback, Faculty Seed Fund (IIIT/R&D Office/Seed-Grant/202122/018; VS) for financial support, and the use of ChatGPT in developing analysis code and copyediting.

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