

Emotional Context Changes Segment Memory, Predictions Determine Its Strength

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Emotional Context Changes Segment Memory, Predictions Determine Its Strength

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Abstract

Predictions and emotional context changes each shape how the mind segments experience into the discrete events we remember, yet their interplay remains poorly understood. To investigate this interplay, we had participants encode neutral and emotional image sequences under uncertainty about whether and when the emotional context would change, while they reported moment-to-moment predictions of negativity. Emotional context changes segmented memories, as indexed by the dilation of later temporal distance judgments. Crucially, segmentation was reduced when predictions were compatible with upcoming emotional context changes and amplified when they were not. Predictions alone, however, did not segment memories when context remained stable. These findings reconcile context-based and prediction-based accounts by showing that context changes drive segmentation, whereas predictions determine its magnitude.

Keywords: event segmentation, episodic memory, context, prediction, emotion

The ability of our minds to divide continuous experiences into meaningful event units is known as event segmentation (Zacks, 2020; Zacks et al., 2007). Events are often conceptualized as temporally extended units defined by stable contexts (Clewett & Davachi, 2017; Clewett et al., 2019). Contextual stability may be derived from external features, such as stimulus category or background information, as well as internal features, such as emotion or inferences about the situation (DuBrow & Davachi, 2013, 2014, 2016; Shin & DuBrow, 2021; Y. C. Wang et al., 2024). Changes in stable contexts create event boundaries, which, in turn, shape the temporal structure of episodic memories (Güler et al., 2025; Pu et al., 2022).

Temporal structuring via event boundaries is reflected in the temporal distance and order of memories. Typically, memory instances that are separated by a boundary are judged farther apart in time (temporal dilation), whereas those within the same event are judged closer (temporal compression) (Bangert et al., 2020; Ezzyat & Davachi, 2014; T. Wen & Egner, 2022). People also tend to recall the order of instances more accurately when they are within the same event than when they span an event boundary (Horner et al., 2016; Pu et al., 2022), except when contextual information is accessible at retrieval (Ding & Zacks, 2026; T. Wen & Egner, 2022).

Emotion is one of the prominent contextual features that influences how events are segmented and remembered (Chen & Swallow, 2025; Dev et al., 2022; McClay et al., 2023; Petrucci & Palombo, 2021; Sachs et al., 2025; Sherrill et al., 2019; Talmi & Palombo, 2025; J. Wang & Lapate, 2025; J. Wang et al., 2022; Y. C. Wang et al., 2024; Zhou et al., 2026). However, only a few studies have investigated how changes in emotional context drive event segmentation and shape temporal memory (McClay et al., 2023; J. Wang & Lapate, 2025).

First, McClay et al. (2023) investigated how changes in emotional states, induced by music, influence the temporal organization of memory for concurrently encoded neutral images. They showed that transitions toward relatively more positive emotional states promoted temporal integration, reflected in improved temporal order accuracy and compressed temporal distance judgments, whereas transitions toward relatively more negative states led to segmentation, reflected in reduced temporal order accuracy and temporal dilation.

Second, J. Wang and Lapate (2025) examined how transitions between events, defined by sequences of either neutral or emotional (negative high-arousal) images, shape temporal memory. They found that images encoded within the same emotional event were remembered as temporally compressed, whereas transitions from neutral to emotional events produced temporal dilation. Moreover, when the order of two images was tested, accuracy was higher if the more recently encoded one was emotional, whether they came from the same or different events, suggesting that emotional salience can support order accuracy.

Understanding of how emotional event transitions shape temporal memory is crucial; yet, a key element in this equation may be missing: predictions (Lohnas & Howard, 2025; J. Wang & Lapate, 2025). Predictions strongly influence how an experience is encoded by determining the precision and structural organization of memory (Bein et al., 2023; Huang et al., 2025; Poskanzer et al., 2025; Sinclair et al., 2021; Wahlheim & Zacks, 2025; Yao et al., 2026). According to event segmentation theory, an event is assumed to continue as long as predictions remain compatible with the unfolding experience (Zacks et al., 2007). Conversely, prediction violations signal an event boundary (Antony et al., 2021; Bağlar & Günseli,

2026; Nolden et al., 2024; Rouhani et al., 2020; Su et al., 2026; Zacks et al., 2011). Recent work extends this perspective and shows that prediction uncertainty, defined as reduced confidence in predictions, is another important factor influencing how events are segmented (Baldwin & Kosie, 2021; Nguyen et al., 2024, 2026; Yao et al., 2026). While predictions shape event cognition and memory, their role during uncertain and dynamic *emotional* event transitions remains underexplored.

Accordingly, the main aim of our study was to examine how predictions interact with uncertain emotional event transitions to influence segmentation and temporal memory. Given that individual differences may affect how people generate predictions and segment their experiences, as an exploratory question, we also examined whether these interactions differ across varying levels of trait anxiety and dispositional optimism (Eisenberg et al., 2016, 2023; Pitts et al., 2022; J. Wang & Lapate, 2025).

Participants encoded image sequences and later completed temporal distance and temporal order memory tests in each block (DuBrow & Davachi, 2013; Ezzyat & Davachi, 2014). Encoding consisted of six image sequences representing events. These events were either neutral or emotional, and varied in length and order to increase uncertainty. Critically, during encoding, participants reported their moment-to-moment predictions about how likely a negative image would appear soon, allowing us to test whether predictions modulate temporal memory. We hypothesized that predictions compatible with the emotionality of the upcoming event would weaken segmentation effects on temporal memory, whereas incompatible predictions would strengthen them.

Methods and Procedure

Participants

We obtained ethical approval from the university ethics council. We recruited participants through the university's online research participation system and online campus announcements. All participants provided written informed consent before the study. Participants received course credits for their participation.

We targeted a final sample of 90 participants, consistent with sample sizes reported in comparable studies examining emotional transitions and temporal memory (McClay et al., 2023; J. Wang & Lapate, 2025). A total of 92 participants were recruited. Two participants did not complete the study, one due to a technical error and one due to the emotional intensity of the stimuli, resulting in a final sample of 90. The sample consisted of 69 women, 19 men, and 2 nonbinary individuals. The mean age was 22.13 years ($SD = 2.82$). 71 participants reported no prior psychiatric diagnosis. The remaining 19 reported at least one diagnosis, including anxiety disorders ($n = 11$), obsessive-compulsive disorder (OCD; $n = 3$), posttraumatic stress disorder (PTSD; $n = 1$), attention-deficit/hyperactivity disorder (ADHD; $n = 1$), depression ($n = 1$), and anxiety comorbid with either ADHD or OCD ($n = 2$).

Stimuli

We obtained the neutral and emotional images from the Set of Fear Inducing Pictures (SFIP) developed within the Nencki Affective Picture System (NAPS; Marchewka et al., 2014; Michałowski et al., 2017).

The neutral images structuring neutral events were randomly selected for each participant from a pool of 692 neutral images. These images predominantly depicted people, animals, objects, scenes, and food in everyday contexts. The emotional images structuring emotional events were randomly selected for each participant from a pool of 80 negative and high-arousal images in the blood-category subset of SFIP. This category was selected because its content, depicting injured, ill, or deceased people and animals, bloody objects, and scenes of crime, accidents, or death, more closely resembles the neutral image pool in semantic content compared to other negative image categories in SFIP.

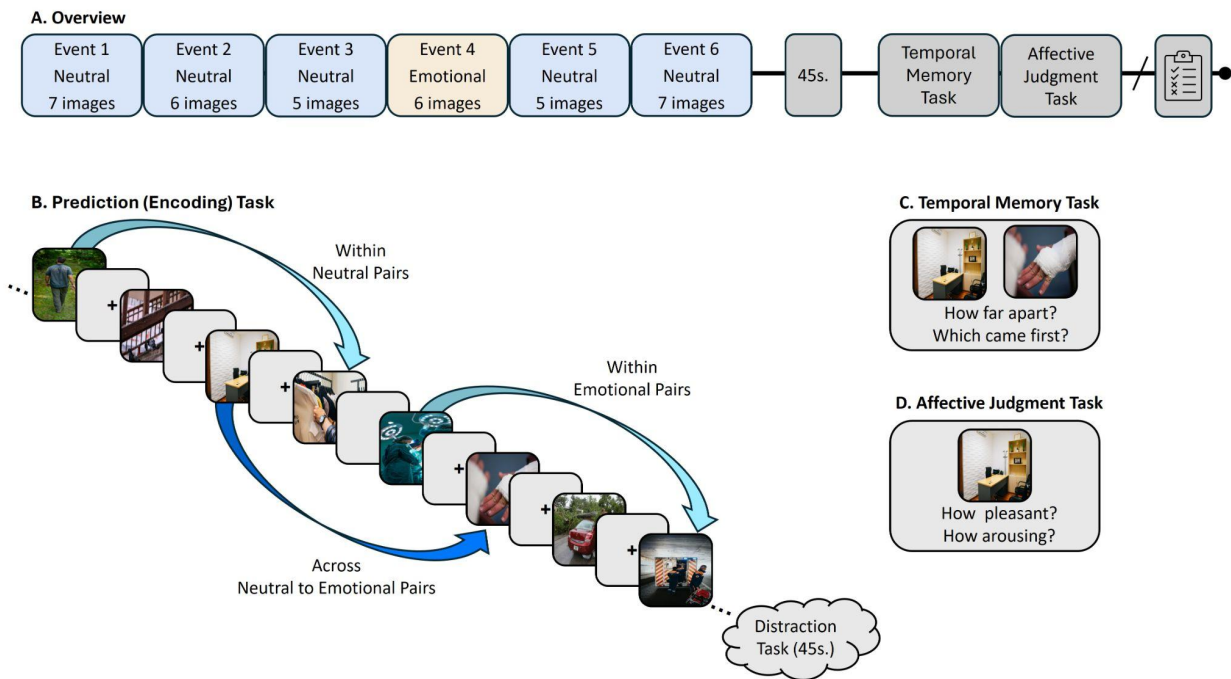


Figure 1. (A) An example block and the overall flow of the experiment are represented. Each block began with a prediction task, during which six events were encoded, followed by a distraction task, the temporal memory task, and the affective judgment task, making up one block. After 12 blocks, participants completed the psychological measures. Here, the number, position, and length of emotional events are only an example and varied across blocks. (B) In the prediction task, the images making up each event appeared one at a time, and participants encoded them while rating how likely a negative image would appear soon, from 1 (very unlikely) to 4 (very likely), giving a moment-to-moment measure of predicted negativity. A fixation cross followed each image, replaced by a blank screen at the transition between events. The arcs mark example image pairs later tested for memory. (C) For each selected image pair, participants judged how far apart in time the two images had appeared, from 1 (very close) to 4 (very far), and then which came first, using the left or right arrow key. (D) Participants rated each image for pleasantness, from 1 (very unpleasant) to 9 (very pleasant), and arousal, from 1 (very calm) to 9 (very aroused). Images shown are illustrative and were not used in the study (actual stimuli were from the SFIP within NAPS). Illustrative photographs by Kelvin Yan, Chalo Garcia, Jed Owen, Mathurin Napoly, Daniel Lloyd Blunk-Fernández, Mick Haupt, Akram Huseyn, and Charles Deluvio, used under the Unsplash License.

Procedure

The study consisted of two phases: an experimental phase and a psychological measures phase. In the first phase, participants completed an event segmentation paradigm comprising 12 blocks. In each block,

participants completed four tasks in the following order: a prediction task, a calculation task, a temporal memory task, and an affective judgment task. In the second phase, participants were directed to an online questionnaire to complete the psychological measures (see Fig. 1A).

The following tasks were part of the experimental phase.

1. Prediction Task (see Fig. 1B). The aim of this task was for participants to encode pseudorandomly ordered neutral and emotional events of variable length while simultaneously reporting moment-to-moment predictions of negativity. Each image was displayed at 300×300 pixels for 2.5 seconds. During the presentation of each image, participants rated how likely they thought a negative image would appear soon using number keys on a 4-point rating scale (1 = very unlikely, 2 = unlikely, 3 = likely, 4 = very likely). This response served both to collect moment-to-moment prediction data and to direct participants' attention to the images. Following each image, a fixation cross was presented at the center of the screen for 2 seconds. At transitions between events, the fixation cross was replaced by a blank screen for 2 seconds.

At the beginning of the task, participants were instructed to encode image sequences while providing prediction ratings. Specifically, they were told to focus on the images and the fixation cross that followed each image. Importantly, they were informed that a blank screen would indicate that a sequence had ended, and that sequence lengths and the emotional direction of transitions could vary. They were also encouraged to create a narrative to help them remember the images as they appeared.

Across the 12 blocks, four blocks consisted entirely of six neutral events (6N block type), four blocks contained one emotional event (1E5N block type), and four blocks contained two emotional events (2E4N block type). Varying the number of emotional events across these block types ensured that participants could not predict whether or how many emotional events would appear in a given block.

The order of the 12 blocks was partially constrained. Specifically, the first three blocks included one block of each type (6N, 1E5N, 2E4N), with the order of these three blocks randomized across participants. This ensured that participants were exposed to all block types early in the experiment and prevented their expectations from becoming fixed on a single block type. The remaining nine blocks were presented in a fully randomized order.

Each of the 12 blocks contained six events. The order of events within each block, that is, which event type would follow which, was pseudorandomized. First, to ensure that meaningful prediction data could be collected for emotional events, emotional events were never placed first within a block. Second, in blocks containing two emotional events (2E4N), emotional events were never presented consecutively, because emotional-to-emotional transitions were not of analytical interest in this study, and this constraint maximized the number of neutral-to-emotional event transitions available for the memory tests.

Within each block, event lengths were 5, 6, or 7 images, with each length occurring twice. Varying event length was intended to create uncertainty about when one event would end and another would begin. Because emotional events were fewer in number than neutral events, they were assigned to 6- and 7-image events to maximize the number of images belonging to emotional events and, consequently, the availability of emotional images for the memory tests.

2. Calculation (Distraction) Task (see Fig. 1A). The aim of this task was to minimize potential recency effects from the prediction task and to provide a neutral interval before the subsequent memory test. During this task, participants were repeatedly presented with two randomly selected numbers between 1 and 50 and were asked to calculate their sum. The task lasted 45 seconds.

3. Temporal Memory Task (see Fig. 1C). This task aimed to measure participants' temporal distance and temporal order memory, as indices of event segmentation in memory. First, each selected image pair from the prediction task was presented on the screen, and participants were asked to evaluate their perceived temporal distance by answering the question, "How far apart were these images?" Participants reported their temporal distance judgments using number keys on a 4-point rating scale ranging from 1 (very close) to 4 (very far). Next, the same image pair was presented again, and participants were asked to indicate which image appeared earlier by pressing the left or right arrow keys. Across trials, the left-right position of the images within each pair was randomized. Participants had up to 8 seconds to respond to each question type.

The image pairs used in this task were selected from the encoded events according to fixed rules. There were always two intervening images for each selected test image pair. The two images in a pair were selected either from the same event (within-event pairs) or from two adjacent events (across-event pairs). Within-event pairs were selected as follows: for 5-image events, possible pairs were 1–4 and 2–5; for 6-image events, 1–4, 2–5, and 3–6; for 7-image events, 1–4, 2–5, 3–6, and 4–7, where the numbers indicate each image's serial position within the event. For across-event pairs, possible pairs consisted of the last three images of the preceding event and the first three images of the following event: for 5-image events, 3–1, 4–2, and 5–3; for 6-image events, 4–1, 5–2, and 6–3; for 7-image events, 5–1, 6–2, and 7–3, where the first number refers to the position of an image in the preceding event and the second to the following event.

As a result of this image pair selection rule, the same image could be part of both within and across-event test pairs. To prevent this from introducing any systematic bias or unwanted influence on memory performance, the order of the selected pairs was shuffled such that pairs containing the same image were not tested consecutively.

In each block, participants responded to temporal distance and temporal order questions for 9 image pairs. Accordingly, a total of 54 within-event and 54 across-event image pairs were used across the experiment. Within-event pairs were divided into two categories: within-neutral and within-emotional. Across-event pairs were divided into two categories: across-neutral and across-neutral-to-emotional. Image pairs spanning emotional-to-neutral transitions were not included in the memory test for two reasons. First, this elimination ensured a balanced number of memory test trials across pair types. Second, because emotional events were never followed by another emotional event, emotional-to-neutral transitions were predictable and therefore not relevant to the research question. As a result, of the 54 within-event image pairs, 27 were within-neutral, and 27 were within-emotional, whereas of the 54 across-event image pairs, 27 were neutral-to-neutral and 27 were neutral-to-emotional.

4. Affective Judgment Task (see Fig. 1D). The aim of this task was to measure participants' subjective emotional responses to the images presented during the block. The images were presented one by one at the center of the screen, and participants were asked to answer two questions for each image. The first

question asked how unpleasant or pleasant they felt when they first saw the image, and participants responded using number keys on a 9-point scale ranging from 1 (very unpleasant) to 9 (very pleasant). The second question asked how calm or aroused they felt, and participants responded using number keys on a 9-point scale ranging from 1 (very calm) to 9 (very aroused). In this task, all images from the relevant block were presented in a randomized order, and responses were self-paced.

The following inventories were part of the psychological measures phase.

1. State-Trait Anxiety Inventory-Trait Subscale (STAI-T; Spielberger, 1983). The STAI-T assesses relatively stable individual differences in the tendency to experience anxiety in response to potential threats. The scale consists of 20 items (e.g., "I have disturbing thoughts"; "I feel nervous and restless"). Participants responded on a 4-point rating scale ranging from 1 (almost never) to 4 (almost always). Higher scores indicate greater trait anxiety. Trait anxiety scores used in the analyses were derived from the STAI-T total score.

2. Revised Life Orientation Test (LOT-R; Scheier et al., 1994). The LOT-R assesses dispositional optimism, that is, the general tendency to expect positive rather than negative outcomes across situations. The scale consists of 10 items, 6 of which are scored (e.g., "In uncertain times, I usually expect the best"; "I am always optimistic about my future"), and 4 filler items. Participants responded on a 5-point Likert scale ranging from 0 (strongly disagree) to 4 (strongly agree). Higher scores indicate greater dispositional optimism. Dispositional optimism scores used in the analyses were derived from the LOT-R total score.

Data Analysis

Prior to analyses, we set two exclusion criteria. First, participants who failed to respond on more than 25% of prediction task trials were to be excluded. Second, participants performing at or below chance level (50%) on temporal order accuracy were to be excluded. No participants met either criterion.

All statistical analyses were conducted in R using the lme4, lmerTest, emmeans, car, and MuMIn packages (Bartoń, 2025; Bates et al., 2015; Fox & Weisberg, 2019; Kuznetsova et al., 2017; Lenth, 2025). Continuous outcome variables were analyzed using linear mixed-effects models (LMMs), and binary outcome variables were analyzed using generalized linear mixed-effects models (GLMMs). For all models, random effects were specified as random intercepts for participants, with blocks nested within participants (1 | SubjectNumber/BlockNumber). This structure was preferred over nesting by block type (6N, 1E5N, 2E4N), as block number offered more levels (12 blocks vs. 3 block types), enabling more reliable estimation of variance at the block level. Where multiple comparisons were performed, *p*-values were adjusted using the Holm correction.

In all main analyses, we used trait anxiety as the primary individual difference measure, with dispositional optimism modeled equivalently in supplementary analyses. The trait subscale of the STAI assesses a stable disposition to experience anticipatory worry (Spielberger, 1983). This closely aligns with our central question and positions our findings within work linking hypervigilance, PTSD-related symptomatology, and anxiety to predictive processing, event segmentation, and temporal memory (Eisenberg et al., 2016, 2023; Pitts et al., 2022; Sherrill & Magliano, 2017; J. Wang & Lapate, 2025).

When trait anxiety modulated a focal effect, we probed the interaction at low ($M - 1\ SD$) and high ($M + 1\ SD$) levels of trait anxiety using model-implied simple slopes or contrasts.

To analyze the affective judgment data, we modeled valence and arousal ratings separately. For each outcome, we first fitted a model with image affect type (neutral vs. emotional) as the sole fixed predictor. Here, we aimed to test whether emotional images were rated as more unpleasant and more arousing than neutral images. We then extended each model by adding z-scored trait anxiety and its interaction with image affect type to test whether the difference in subjective ratings between neutral and emotional images varied as a function of individual differences in trait anxiety. An equivalent supplementary model was also run with dispositional optimism replacing trait anxiety (Supplementary Materials 3).

To analyze prediction data, we modeled participants' prediction ratings (i.e., prediction of negativity) as a function of relative position within the event, event affect type (neutral vs. emotional), z-scored trait anxiety, and all their interactions. Relative position was defined as a continuous variable ranging from 0 to 1, reflecting each image's normalized temporal location within its event ($(\text{image position} - 1) / (\text{event length} - 1)$). Here, our aim was to characterize how predictions of negativity changed as events unfolded, and whether this trajectory differed by event affect type and trait anxiety. We hypothesized predictions of negativity to be higher overall for emotional events than for neutral events. For neutral events, we hypothesized predictions of negativity to increase toward the end of the event, reflecting growing uncertainty about an upcoming event being emotional. For emotional events, we hypothesized predictions of negativity to decrease toward the end of the event, reflecting a growing likelihood of a subsequent neutral event. To capture potential nonlinear changes in predictions of negativity, we included both linear and quadratic polynomial terms of relative position. We compared the linear-only model against the quadratic model using a likelihood ratio test. The better-fitting model was used for inference. An equivalent supplementary model was run with dispositional optimism replacing trait anxiety (Supplementary Materials 5).

To analyze the prediction response time data, we modeled response time using a polynomial structure, including linear and quadratic terms of relative position, event affect type (neutral vs. emotional), z-scored trait anxiety, and all their interactions. Here, we aimed to test whether prediction response times varied systematically across the course of an event, and whether this pattern differed by event affect type and trait anxiety. We expected response times to be elevated at event boundaries, that is, the onset of each event, reflecting the cost of updating the current event model (DuBrow & Davachi, 2013; Morse et al., 2023; Radvansky & Zacks, 2017; Richmond & Zacks, 2017), and to decrease as the ongoing event representation became more established. We also expected response times to increase again toward the end of events, reflecting growing prediction uncertainty that precedes event segmentation (Baldwin & Kosie, 2021; Nguyen et al., 2024, 2026; Zacks et al., 2011). Critically, the first event of each block was excluded from this analysis to control for block-onset orienting effects. An equivalent supplementary model was run with dispositional optimism replacing trait anxiety (Supplementary Materials 7).

Before analyzing the temporal memory data, we accounted for semantic similarity between image pairs. Emotional images tend to be more semantically similar to one another, and this similarity could influence temporal memory outcomes (Lohnas & Howard, 2025; Talmi & Palombo, 2025; J. Wang & Lapate, 2025). To do so, we calculated semantic similarity scores for each possible pair and entered them as a covariate in all temporal distance judgment and temporal order accuracy models. To calculate these

scores, we extracted features from two pretrained deep neural networks, VGG-16 and ResNet-50. For VGG-16, we extracted activations from the fc2 layer, which has been shown to align with neural activity in the inferior temporal cortex (Schrimpf et al., 2020). For ResNet-50, we extracted activations from the global average pooling layer, which encodes high-level visual features and has been used to model cortical representations of visual information (He et al., 2016; H. Wen et al., 2018). To reduce the dimensionality of the extracted feature vectors, we applied principal component analysis (PCA). Pairwise similarity scores were computed as Pearson correlations between the PCA-reduced activation vectors of each image pair, separately for each network. Both networks produced highly correlated similarity scores ($r = .76$), and their outputs were averaged into a single composite score. Consistent with prior work, emotional image pairs showed higher semantic similarity than both neutral and neutral-emotional image pairs (Riberto et al., 2019, 2022; J. Wang & Lapate, 2025; Supplementary Materials 13).

In our first analysis of temporal memory data, we modeled distance judgments and order accuracy separately as a function of pair type, semantic similarity, and the serial position of the later-presented image in each pair (to account for recency effects). Pair type had four levels: within-neutral, within-emotional, across-neutral, and across-neutral-to-emotional. Here, our aim was to test whether emotional context changes produced segmentation effects on temporal memory, as evidenced by within- vs. across-event memory differences. For *temporal distance*, we expected neutral-to-emotional transitions to produce temporal dilation (McClay et al., 2023; J. Wang & Lapate, 2025). For *temporal order accuracy*, although segmentation typically predicts impairment for across-event pairs (Y. C. Wang et al., 2024), this effect may be attenuated for neutral-to-emotional transitions, given that emotional item salience has been shown to support order accuracy (J. Wang & Lapate, 2025). To test these predictions, we specified contrasts comparing within-event pairs against across-neutral-to-emotional pairs, applied separately to each outcome. Within-event pairs included both within-neutral and within-emotional pairs, averaged across both types, as across-neutral-to-emotional pairs span both event types. Supplementary contrasts using only within-emotional pairs as the within-event reference are reported in the Supplementary Materials (14). In addition to neutral-to-emotional event transitions, we examined whether neutral-to-neutral transitions, even in the absence of a contextual change, showed segmentation effects. For this, we contrasted pairs from within-neutral against across-neutral for each outcome.

Our second analysis of temporal memory data focused only on across-event pairs. We modeled distance judgments and order accuracy separately as functions of transition type (neutral-to-neutral vs. neutral-to-emotional), prediction of negativity for that transition (z-scored), trait anxiety (z-scored), and all their interactions. Semantic similarity and the serial position of the later-presented image in each pair were included as covariates. Prediction of negativity for each transition was defined as the mean rating across the last three images of the preceding event. Here, our first aim was to test whether emotional context changes produced stronger segmentation effects on across-event temporal memory, as evidenced by differences between neutral-to-emotional and neutral-to-neutral transitions. For *temporal distance*, we hypothesized greater temporal dilation following neutral-to-emotional than neutral-to-neutral transitions. For *temporal order accuracy*, despite the typical impairment expected from segmentation (Y. C. Wang et al., 2024), neutral-to-emotional transitions could show higher accuracy, given that emotional item salience has been shown to support order memory (J. Wang & Lapate, 2025). Our second aim was to test whether these segmentation effects varied as functions of preceding predictions, and to explore the role of trait anxiety. For neutral-to-emotional transitions, we expected greater temporal compression and higher temporal order accuracy as predictions became more negative. Conversely, for neutral-to-neutral

transitions, we expected greater temporal dilation and impaired temporal order accuracy as predictions became more negative. To interpret these possible interactions, we examined the simple slope of prediction of negativity separately for each transition type. An equivalent supplementary model was run with dispositional optimism replacing trait anxiety (Supplementary Materials 10).

Results

Full ANOVA tables for all models are reported in the Supplementary Materials (1-10). Here we report the results related to our hypotheses and planned contrasts.

Emotional Images Were Unpleasant and Arousing

Affective judgment models showed that emotional images were rated lower in valence ($\beta = -3.46$, $SE = 0.03$, $z = -130.13$, $p < .001$) and higher in arousal ($\beta = 3.45$, $SE = 0.03$, $z = 127.27$, $p < .001$) than neutral images. Trait anxiety did not moderate judgments of valence ($\beta = 0.03$, $p = .24$) or arousal ($\beta = -0.01$, $p = .69$).

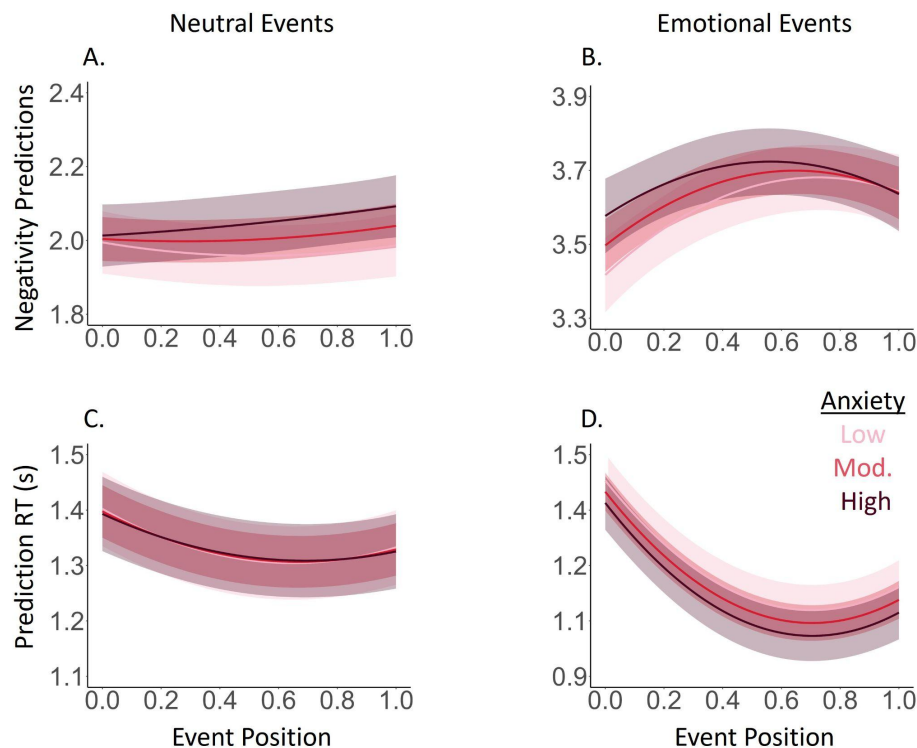


Figure 2. Model-estimated negativity predictions and prediction response times, shown by event type and by position within the event. The top row (A, B) shows the negativity predictions: the y-axis is how likely participants judged a negative image to appear next, from 1 to 4. The x-axis is event position, each image's place within its event from the first image at 0 to the last at 1, on a common scale across the 5-, 6-, and 7-image events. Neutral events are on the left (panel A) and emotional events on the right (panel B). The bottom row (C, D) shows the response times: the y-axis is the response time in seconds, plotted across the same event position. Neutral events are on the left

(panel C) and emotional events on the right (panel D). In every panel, three lines mark trait anxiety at low (-1 SD), moderate (mean), and high ($+1$ SD) levels, shown in light pink, red, and dark red. The y-axes are zoomed and their ranges differ across panels, so the panels are not on a common scale and should not be compared by height. Shaded bands are 95% confidence intervals.

Negativity Predictions Were Sensitive to Event Affect, Event Position, and Trait Anxiety

To select the appropriate model to fit prediction ratings, we compared the linear-only model with one including quadratic terms to capture potential nonlinear dynamics. The latter provided a better fit, $\chi^2(4) = 27.89$, $p < .001$, and was therefore used for all subsequent analyses. This model showed that participants predicted more negativity during emotional than neutral events ($\beta = 1.62$, $SE = 0.01$, $z = 141.23$, $p < .001$). During neutral events, prediction of negativity increased linearly as the events unfolded ($\beta = 2.41$, $SE = 0.90$, $z = 2.69$, $p = .01$), with no significant quadratic trend ($\beta = 1.59$, $p = .08$). This trajectory indicates that participants increasingly anticipated an emotional transition as the neutral events unfolded. During emotional events, prediction of negativity initially increased and then decreased ($\beta_{linear} = 9.58$, $SE = 1.97$, $z = 4.87$, $p < .001$; $\beta_{quadratic} = -9.53$, $SE = 1.97$, $z = -4.84$, $p < .001$), following an inverted-U pattern. This suggests that participants initially updated their predictions toward negativity, then began to anticipate a return to neutrality as the emotional event progressed (see Fig. 2A-B).

Trait anxiety modulated these prediction trajectories. In neutral events, predictions remained stable at low trait anxiety (-1 SD; $\beta = -0.29$, $p = .82$), whereas at high trait anxiety ($+1$ SD), predictions of negativity increased as the events progressed ($\beta = 5.09$, $SE = 1.26$, $z = 4.04$, $p < .001$); this difference was significant ($\beta = -5.39$, $SE = 1.78$, $z = -3.02$, $p = .003$). Trait anxiety thus drove anticipation of an emotional transition during neutral events. In contrast, during emotional events, the initial increase in prediction of negativity was strong at low trait anxiety ($\beta = 15.02$, $SE = 2.78$, $z = 5.41$, $p < .001$) but weaker and nonsignificant at high trait anxiety ($\beta = 4.16$, $p = .13$); this difference was significant ($\beta = 10.86$, $SE = 3.91$, $z = 2.78$, $p = .006$). This flatter slope at high trait anxiety may reflect elevated baseline expectations, leaving limited room for further increase (see Fig. 2A-B).

The prediction response time model showed that participants were slower to predict at event beginnings, sped up through the middle, and slowed again toward the end of events, following a U-shaped pattern in both neutral ($\beta = 3.67$, $SE = 0.46$, $z = 8.03$, $p < .001$) and emotional events ($\beta = 12.90$, $SE = 0.90$, $z = 14.26$, $p < .001$). This U-shaped pattern may reflect event model updating at event onsets and growing prediction uncertainty toward event ends. The U-shape was more pronounced in emotional than neutral events ($\beta = 9.23$, $SE = 1.01$, $z = 9.11$, $p < .001$), possibly due to greater event model updating costs imposed by context changes. Trait anxiety only interacted with event affect type, such that higher anxiety was associated with relatively faster responses in emotional than in neutral events ($\beta = -0.03$, $SE = 0.006$, $z = -5.53$, $p < .001$). Elevated baseline negativity predictions in high-anxiety participants may have sped up their responses (see Fig. 2C-D).

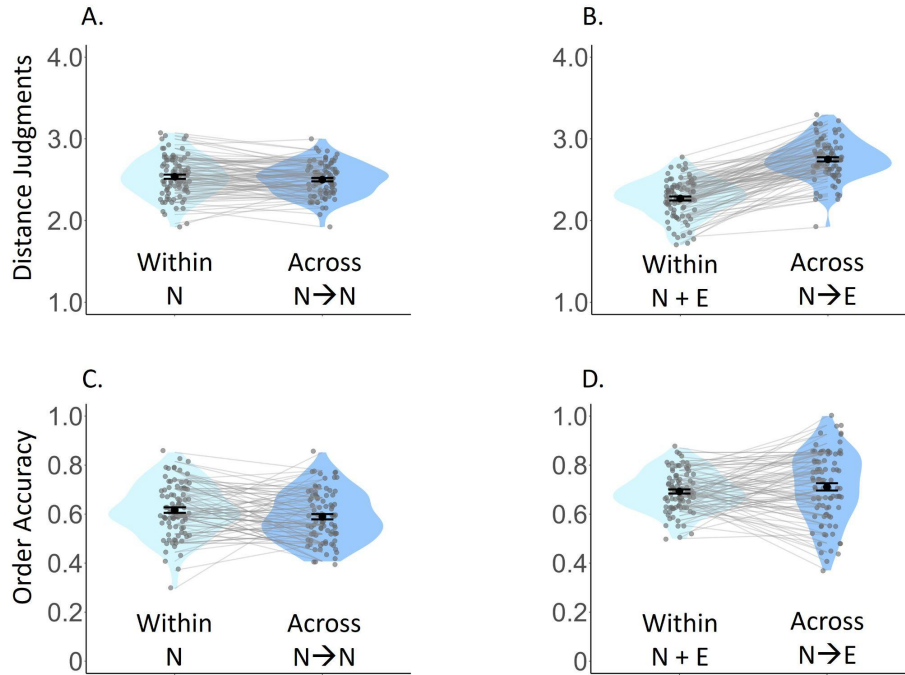


Figure 3. *Temporal memory for within-event and across-event image pairs, shown for each transition type. The top row (A, B) shows temporal distance judgments on the y-axis, where higher values mean the two images were judged farther apart in time, from 1 to 4. The x-axis contrasts within-event pairs with across-event pairs. The left panel (A) compares within-neutral pairs (Within N) with across-neutral pairs (Across N→N), and the right panel (B) compares within-event pairs, averaged across-neutral and emotional events (Within N+E), with across neutral-to-emotional pairs (Across N→E). The bottom row (C, D) shows temporal order accuracy on the y-axis, the proportion of pairs ordered correctly, from 0 to 1, for the same two comparisons: within-neutral versus across neutral pairs on the left (C), and within-event versus across neutral-to-emotional pairs on the right (D). Within-event pairs are light blue and across-event pairs are darker blue. The violins show the spread of participants' mean scores, the gray points are individual participants, and the thin gray lines join the same participant across the two conditions. The black point shows the group means, with bars for ± 1 standard error.*

Emotional Context Changes and Predictions Jointly Segment Memories

Within- vs. Across-event Temporal Memory

In our first analysis of temporal memory, we used planned contrasts to test segmentation through within- vs. across-event differences. For *temporal distance*, neutral-to-emotional transitions produced temporal dilation, with across-event pairs judged farther apart than combined within-event pairs (emotional and neutral) ($\beta = 0.46$, $SE = 0.02$, $z = 25.58$, $p < .001$). A supplementary contrast comparing neutral-to-emotional across-event pairs specifically against within-emotional pairs similarly yielded a dilation effect (see Supplementary Materials 14). This indicates that emotional context changes segmented memory. Neutral-to-neutral transitions showed no significant difference for temporal distance judgments between across- and within-event pairs ($\beta = -0.035$, $p = .08$). Without an emotional context change, segmentation did not emerge (see Fig. 3A-B).

For *temporal order accuracy*, neutral-to-emotional transitions did not differ from combined within-event pairs (emotional and neutral) ($OR = 1.09$, $p = .15$). However, a supplementary contrast between neutral-to-emotional across-event pairs and within-emotional pairs revealed lower order accuracy for across-event pairs (see Supplementary Materials 14). This may reflect that segmentation was specific to comparisons against within-emotional pairs. This pattern may have emerged due to the higher temporal order accuracy of within-emotional pairs, given that emotional contexts have been shown to enhance within-event temporal binding (Clewett & McClay, 2025; Y. C. Wang et al., 2024). Neutral-to-neutral transitions showed no significant difference in temporal order accuracy between across- and within-event pairs ($OR = 0.89$, $p = .09$), again indicating no segmentation effect in the absence of an emotional context change (see Fig. 3C-D).

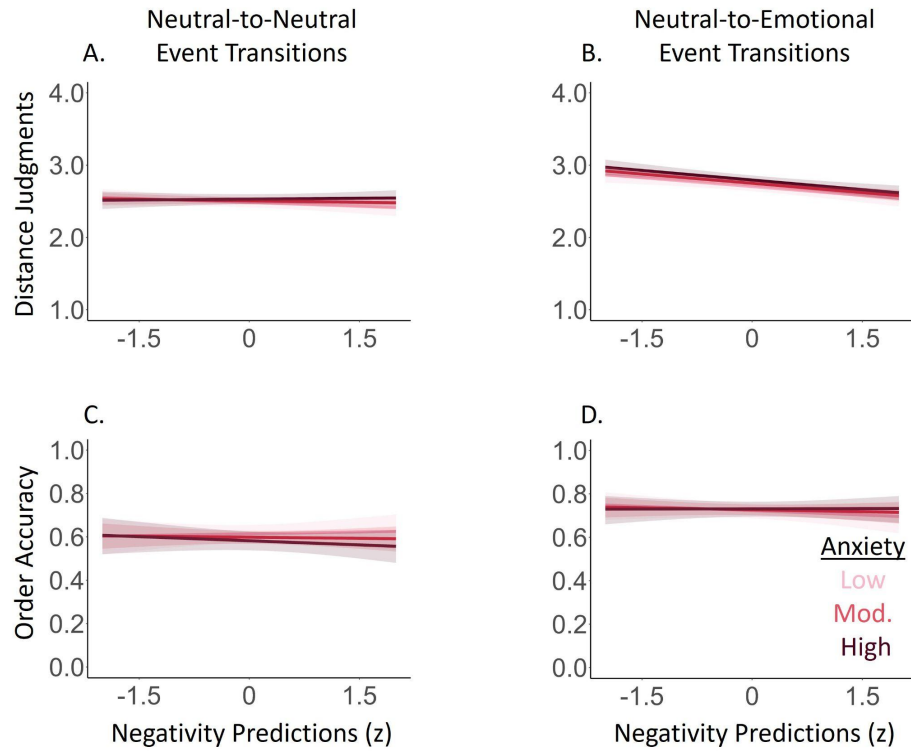


Figure 4. *Temporal memory for across-event pairs as a function of the prediction of negativity, shown for each transition type. The top row (A, B) shows distance judgments on the y-axis, where higher values mean the two images were judged farther apart in time, from 1 to 4. The x-axis is the predicted negativity, taken as the average of the last three predictions of the preceding event and z-scored across the sample. Neutral-to-neutral transitions are on the left (panel A) and neutral-to-emotional transitions on the right (panel B). The bottom row (C, D) shows order accuracy on the y-axis, the probability of judging the order correctly, from 0 to 1, plotted across the same predicted negativity. Neutral-to-neutral transitions are on the left (panel C) and neutral-to-emotional transitions on the right (panel D). In every panel, the three lines are model estimates at low (-1 SD), moderate (mean), and high (+1 SD) trait anxiety, shown in light pink, red, and dark red. Shaded bands are 95% confidence intervals.*

Prediction Compatibility and Across-event Temporal Memory

In our second analysis of temporal memory, we focused on across-event pairs to test whether emotional transitions produced stronger segmentation than neutral transitions and whether predictions modulated it. For *temporal distance*, neutral-to-emotional pairs were judged farther apart in time than neutral-to-neutral pairs ($\beta = 0.24$, $SE = 0.02$, $z = 11.08$, $p < .001$), extending the segmentation effect beyond within-event pairs reported above. Crucially, when participants predicted more negativity before an emotional transition, the temporal dilation was reduced ($\beta = -0.085$, $SE = 0.016$, $z = -5.32$, $p < .001$). Thus, anticipating an emotional shift weakened its segmentation effect. This relationship between predictions and temporal dilation was not observed for neutral-to-neutral transitions ($\beta = -0.014$, $p = .42$), showing that predictions modulated segmentation only in the presence of an emotional context change. Trait anxiety did not influence temporal distance judgments ($\beta = 0.034$, $p = .10$) or their modulation by predictions ($\beta = -0.025$, $p = .25$; see Fig. 4A-B).

For *temporal order accuracy*, neutral-to-emotional pairs were ordered more accurately than neutral-to-neutral pairs ($OR = 1.79$, $SE = 0.13$, $z = 8.14$, $p < .001$). Contrary to typical segmentation predictions, emotional context changes enhanced rather than impaired temporal order memory. Prediction of negativity did not influence order accuracy in either transition type, suggesting that the modulation of segmentation by predictions was specific to temporal distance. Trait anxiety did not influence order accuracy ($OR = 0.98$, $p = .65$), as it did not for temporal distance judgments (see Fig. 4C-D).

Discussion

We examined how predictions interact with emotional context changes to shape temporal memory using a modified event segmentation paradigm. The paradigm introduced uncertainty about whether the emotional context would change while measuring moment-to-moment predictions. Emotional context changes segmented memories, reflected in increased temporal distance judgments. Crucially, these effects were modulated by participants' predictions: segmentation was reduced when emotional context changes were compatible with the predictions and amplified when they were not. These findings suggest that temporal memory is structured by the interplay between two forces of event segmentation: context changes and accompanying predictions.

We found that emotional context changes, here defined as shifts in stimulus valence and arousal, segment memories. Transitions across events generated temporal dilation when the emotion shifted, but not when it remained stable. This segmentation effect persisted after controlling for higher semantic similarity among emotional images. These findings replicate prior evidence on temporal dilation across emotional transitions (McClay et al., 2023; J. Wang & Lapate, 2025). More broadly, they are consistent with accounts linking context changes to event segmentation (Bağlar & Günseli, 2026; Clewett & Davachi, 2017; Güler et al., 2025; Pu et al., 2022).

Prediction compatibility modulated the segmentation effect driven by changes in emotional context. Participants who predicted more negativity perceived neutral-to-emotional transitions as less distant, suggesting that anticipating the change reduced the segmentation effect. However, prediction errors were

not sufficient to produce segmentation when the emotional context remained stable: participants who predicted negativity did not perceive neutral-to-neutral transitions as more temporally distant, despite presumably experiencing prediction errors. These findings suggest that predictions can *modulate* memory segmentation but cannot *generate* it without accompanying context changes (Cheng et al., 2026; Güler et al., 2025; Schapiro et al., 2013; Shim et al., 2024).

These memory-segmentation effects may stem from how event-model updating is driven by context changes and modulated by predictions. Accordingly, prediction response time at event onsets, which may reflect event-model updating, was longer after an emotional context change than when the context remained stable (Supplementary Materials 11). Moreover, response times were reduced when emotional context changes were compatible with predictions and increased when they were not (Supplementary Materials 12). Thus, when the emotional context changes, the current event model's predictions may no longer hold. This may prompt a model update (Bailey et al., 2017; Richmond & Zacks, 2017; Zhou et al., 2026) and the consolidation of the just-encoded event as a distinct memory unit (Silva et al., 2019; Zheng et al., 2022). Both the model update and its effects on memory organization may be modulated by how well participants predicted the context change (Antony et al., 2021; Clewett et al., 2019; Ezzyat & Clements, 2024). In contrast, when the context remains stable across neutral events, the existing event model may largely remain applicable, and no update is triggered. Although violation of predictions toward an emotional event may produce a momentary prediction error when no emotional transition follows, the accumulating evidence of contextual stability suggests that an event-model update is not warranted (Clewett et al., 2025; Güler et al., 2025; Sasmita & Swallow, 2024).

An alternative account is binding through shared context. Shared contextual representation may bind co-occurring information together, making them more accessible to one another at retrieval and perceived closer in time, compared to information across different contexts (Clewett & Davachi, 2017; Clewett et al., 2019; Ezzyat & Davachi, 2014; Howard & Kahana, 2002; Lohnas & Howard, 2025; Polyn et al., 2009). Reactivation of the just-encoded event at boundaries may further strengthen within-event bindings (Güler et al., 2026; Silva et al., 2019; Sols et al., 2017; for a review, see Günseli, 2026). When a context change is predicted, the upcoming context can be actively represented before the actual transition (Ezzyat & Clements, 2024; Lee et al., 2021). From a context-binding perspective, this joint representation of successive contexts could bind them together, reducing their perceived temporal distance. When the context remains stable, images stay bound by their context, limiting the influence of any initially predicted context representation.

Whereas temporal distance judgments were influenced by context changes and predictions consistent with segmentation accounts, temporal order accuracy showed an opposite pattern. Contrary to boundary-driven impairment in temporal order previously observed in the literature (McClay et al., 2023; Y. C. Wang et al., 2024), order accuracy was increased when the emotional context changed (J. Wang & Lapate, 2025). Moreover, segmentation scores for the temporal distance and order measures (within- vs across-event pair differences) were uncorrelated across individuals (J. Wang & Lapate, 2025; Supplementary Materials 15). This dissociation may arise from emotion-related memory processes that overrode the segmentation effect on order accuracy. First, the emotional images are often encoded more strongly than neutral images (Kensinger & Corkin, 2003; LaBar & Cabeza, 2006), and item strength can serve as a recency signal that supports temporal order judgments (DuBrow & Davachi, 2017; Jenkins & Ranganath, 2016). In our neutral-to-emotional pairs, where the emotional image was always the more recently encoded one, this

strength-based recency signal would favor correct order judgments. Second, affective shifts can enhance position memory (Kumar et al., 2026), which may improve order judgments. Lastly, given that the availability of context during retrieval has been shown to allow better order judgments across transitions (Ding & Zacks, 2026; T. Wen & Egner, 2022), the emotional value of probe images could have provided contextual cues that supported order judgments.

Trait anxiety and dispositional optimism dynamically influenced predictions during encoding but not memory segmentation (Supplementary Materials 5 and 10). Several factors may account for this pattern. First, clear and abrupt emotional context changes in the present study may have outweighed possible effects of individual differences in segmentation. In everyday life, by contrast, perceived emotionality may depend more on subjective appraisal, such as interpreting whether a coworker is friendly or passive-aggressive. Moreover, by requiring a negativity prediction on every trial, our prediction task may have heightened attention to abrupt emotional changes and further increased their segmentation (Bailey et al., 2017), plausibly making the segmentation patterns more uniform across participants. Second, both the lack of narrative coherence in our pictorial stimuli (Petrucci & Palombo, 2021; Talmi & Palombo, 2025) and the restricted variability of our non-clinical university sample (Eisenberg et al., 2016) may have left little room for individual differences to be reflected in memory. Future studies using more naturalistic paradigms and diverse samples may better capture how individual differences, predictions, and emotional transitions jointly shape memory segmentation.

In sum, the present study shows that the dynamic interplay between contextual change and predictions shapes temporal memory. Emotional context changes segmented memories as indexed by temporal distance, yet this segmentation was attenuated when participants anticipated the change and amplified when they did not. On the other hand, prediction errors without context changes were insufficient to generate segmentation. Notably, temporal distance and temporal order accuracy showed dissociable patterns, suggesting these measures capture distinct aspects of episodic memory. Together, these findings underscore how the contextual shifts we encounter and the predictions we carry into them jointly shape the structure of episodic memory.

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