EVENT SEGMENTATION IN EPISODIC MEMORY: THE ROLE OF PREDICTION ERRORS, CONTEXTUAL TRANSITIONS, AND AFFECTIVE MODULATION

by
BERNA GÜLER

Submitted to the Graduate School of Social Sciences
in partial fulfilment of
the requirements for the degree of Doctor of Philosophy

Sabancı University
June 2025

EVENT SEGMENTATION IN EPISODIC MEMORY: THE ROLE OF PREDICTION ERRORS, CONTEXTUAL TRANSITIONS, AND AFFECTIVE MODULATION

Approved by:

Asst. Prof. EREN GÜNSELİ ....
(Dissertation Advisor)

Assoc. Prof. ÇAĞLA AYDIN ....

Prof. ALİ İZZET TEKCAN ....

Asst. Prof. DAVID CLEWETT ....

Prof. TİLBE GÖKSUN ....

Date of Approval: June 19, 2025

ABSTRACT

EVENT SEGMENTATION IN EPISODIC MEMORY:
THE ROLE OF PREDICTION ERRORS, CONTEXTUAL TRANSITIONS,
AND AFFECTIVE MODULATION

BERNA GÜLER

Experimental Psychology, Ph.D. Dissertation, June 2025

Dissertation Supervisor: Asst. Prof. EREN GÜNSELİ

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

Episodic memory allows us to structure continuous experience into discrete, meaningful events, yet the mechanisms that shape segmentation and how different factors influence this process are not fully understood. This thesis investigates how prediction errors, contextual stability, and affective processes influence event segmentation. Across a series of behavioral experiments, I show that stable contextual information plays a more critical role in triggering event boundaries than prediction errors alone. Furthermore, while high-reward associations during the ongoing experience can enhance memory, they do not consistently alter the segmented structure of the experience. Finally, I demonstrate that retrospective cognitive reappraisal of emotional events can reorganize how past experiences are segmented and remembered. Together, these findings challenge traditional models that emphasize prediction errors and highlight the flexible, dynamic nature of memory organization shaped by both bottom-up and top-down influences.

ÖZET

EPİZODİK BELLEKTE OLAY SEGMENTASYONU:
TAHMİN HATALARININ, BAĞLAMSAL GEÇİŞLERİN VE DUYGU
DÜZENLEMENİN ROLÜ

BERNA GÜLER

Deneysel Psikoloji, Doktora Tezi, Haziran 2025

Tez Danışmanı: Dr. Öğr. Üyesi EREN GÜNSELİ

Anahtar Kelimeler: olay segmentasyonu, bağlam, tahmin hatası, duygu düzenleme, olaysal bellek

Epizodik bellek, sürekli deneyimlerimizi anlamlı ve ayrık olaylara dönüştürmemizi sağlar. Ancak, olay segmentasyonunu şekillendiren mekanizmalar ve bu süreci etkileyen farklı faktörlerin nasıl işlediği henüz tam olarak anlaşılmamıştır. Bu tez, tahmin hatalarının, bağlamsal stabilitenin ve duygusal süreçlerin olay segmentasyonu üzerindeki etkilerini araştırmaktadır. Davranışsal deneylerden oluşan bir dizi çalışma kapsamında, yalnızca tahmin hatalarından ziyade, stabil bağlamsal bilginin olay sınırlarının ortaya çıkmasında daha kritik bir rol oynadığı gösterildi. Ayrıca, deneyim sırasında yüksek ödül beklentisinin belleği güçlendirebildiği, ancak olay segmentasyonunu tutarlı bir şekilde değiştirmediği görüldü. Son olarak, duygusal olaylara yönelik geriye dönük bilişsel yeniden değerlendirme yoluyla, geçmiş deneyimlerin nasıl segmental olarak yapılandırıldığının ve hatırlandığının yeniden şekillenebileceği gösterildi. Bu bulgular, segmentasyonun oluşumuna dair tahmin hatalarını önceliklendiren geleneksel modelleri sorgulamakta ve bellek organizasyonunun hem aşağıdan yukarı hem de yukarıdan aşağı işlemleme ile şekillenen esnek ve dinamik doğasını vurgulamaktadır.

ACKNOWLEDGEMENTS

The PhD journey is undoubtedly a unique experience for anyone who chooses this path. Yet, in the story of my life, it holds an even more special place. It has been an incredible adventure where I not only grew academically but also evolved as a person. I had the privilege of meeting inspiring people, collecting lifelong friendships, and navigating through existential crises. It was during this journey that I truly witnessed how the flap of a butterfly's wings in one place can create a storm elsewhere—a humbling reminder of how small actions and choices ripple through life. I also learned how much we are bound by time and what it brings to us.

This journey would not have been possible without the unwavering support of my family. Although they often said, "You would be fine and do everything just as well whether we were there for you or not," I know that their encouragement to follow my heart and choose my own path gave me the courage to pursue this dream. They have taught me the value of unconditional support, loving wholeheartedly, sharing generously, staying curious, being organized and responsible, and approaching every person and idea with fairness and open-mindedness. Knowing that there is always a family to catch you when you fall is, without a doubt, life's greatest luxury—and I am profoundly grateful for that. I wouldn't be here without you.

Of course, there is also the family we are not born into but choose along the way—our friends. I consider myself incredibly lucky to have met wonderful people during my master's studies who became dear friends. And just when I thought such luck was rare, life surprised me again during my PhD. I had the privilege of meeting truly amazing individuals who are now among my closest friends. Their colorful spirits, kind hearts, generosity, and resilience continue to inspire me every day. Beyond academic collaborations, sharing life's joys, struggles, laughter, and support made this journey not just meaningful but beautiful. Without you, this would have been a mere journey—thanks to you, it was an adventure. I am endlessly grateful to each and every one of you. You mean far more to me than these pages can ever convey. Just as you were always "there," know that I will always be "here" for you.

In life, beyond the context of academic journeys, you also encounter people along the way who become irreplaceable parts of your story. I am beyond lucky to have friends who have stood by me through every chapter of life. Thank you for understanding me with just a glance, for laughing and crying alongside me, and for facing everything life brings—side by side. Walking these winding roads together, with hope and curiosity, is a privilege I cherish deeply. I also want to express my heartfelt thanks to my long-time companion, who has been a part of my life through many ups and downs, for his constant support and unwavering motivation to always look for what's best for me, no matter the circumstances.

A significant part of my PhD research was conducted at the University of California, Los Angeles (UCLA). I am deeply grateful to David Clewett for his belief in me, for the guidance he provided during a personally difficult period of my life, and for the stimulating discussions that enriched both my thinking and my research. I also feel incredibly lucky to have crossed paths with such a warm and supportive lab team during my time there. I returned to Turkey not only with valuable academic experience but also with beautiful friendships that I will carry with me always. Thank you for your academic and personal support, and for making me feel welcome and at home.

I would also like to sincerely thank the members of my thesis committee for their valuable feedback, close involvement, and continuous support throughout the development of my dissertation. It has been a true privilege to work with each of them and to benefit from their experience.

Finally, I would like to express my sincere gratitude to Eren Günseli, who made it possible for me to pursue a PhD and believed in me from the very beginning. When I applied to Sabancı University, it was my last available option at the time—and the position I most hoped for. Had I not been accepted, I likely would not have continued in academia, as I couldn't afford to wait another year. The countless experiences and gratitude I've expressed throughout this acknowledgement all trace back to Eren's decision to believe in me, to create the opportunity for me to work together, and to welcome me into the lab with kindness and support. This experience has shaped me profoundly—making me more patient, resilient, compassionate, confident, and knowledgeable. Eren taught me not only how to enjoy life more but also how to grow as a researcher and as a person in this demanding academic world. Words will never fully capture the depth of my gratitude, but I offer my most sincere thanks from the bottom of my heart. It was a privilege to work with you—and it always will be.

Lastly, I want to (half-jokingly) thank myself for remaining open to growth, embracing change, and navigating the ups and downs of a Ph.D. It wasn't a rigid path, but the journey was the true reward.

I wholeheartedly dedicate this
work to my family and friends

TABLE OF CONTENTS

ABSTRACT ..... **iv**

ÖZET ..... **v**

LIST OF FIGURES ..... **xii**

1. GENERAL INTRODUCTION **1**
- 1.1. Theories of Event Segmentation 2
- 1.2. What Influences Event Segmentation, and How Does It Affect Episodic Memory 3
- 1.3. Underlying Neural Mechanisms of Event Segmentation 4
- 1.4. Part 1. Underlying Mechanisms of Event Segmentation: Prediction Error vs Contextual Stability 5
- 1.5. Part 2. Online Effects of Reward on Event Segmentation 6
- 1.6. Part 3. Retrospective Effects of Emotion Regulation on Event Segmentation 7
- 1.7. General Aim 8

2. PART 1: UNDERLYING MECHANISMS OF EVENT SEGMENTATION **9**
- 2.1. Introduction 9
- 2.2. Methods 11
  - 2.2.1. Ethical Approval 11
  - 2.2.2. Open Science Practices 11
  - 2.2.3. Participants 11
  - 2.2.4. Stimuli 12
  - 2.2.5. Design 13
    - 2.2.5.1. Experiment 1 13
    - 2.2.5.2. Experiment 2 14
    - 2.2.5.3. Experiment 3 14

2.2.5.4. Experiment 4 16
2.3. Results 16
2.3.1. Experiment 1: Does Prediction Error Generate Event Boundaries? 17
2.3.2. Experiment 2: Does Contextual Stability Generate Event Boundaries? 17
2.3.3. Between-subjects Comparison Across Experiments 1 and 2 17
2.3.4. Experiment 3: Within-subject Replication of Experiments 1 and 2 18
2.3.5. Experiment 4: Does Prediction Error Play a Role? 19
2.4. Discussion 21

3. PART 2: ONLINE EFFECTS OF REWARD ON EVENT SEGMENTATION 25
3.1. Introduction 25
3.2. Methods 27
3.2.1. Ethical Approval 27
3.2.2. Open Science Practices 27
3.2.3. Participants 27
3.2.4. Stimuli 27
3.2.5. Design 28
3.2.5.1. Experiment 1 28
3.2.5.2. Experiment 2 29
3.3. Results 30
3.3.1. Experiment 1: Do Online Changes in Reward Value Generate a Segmentation Difference? 30
3.3.2. Experiment 2: Does Reducing the Strength of Category Transitions Make the Effect of Reward on Segmentation More Apparent? 31
3.4. Discussion 32

4. PART 3: RETROSPECTIVE EFFECTS OF EMOTION REGULATION ON EVENT SEGMENTATION 35
4.1. Introduction 35
4.2. Methods 38
4.2.1. Open Science Practices 38
4.2.2. Ethical Approval 38
4.2.3. Participants 38
4.2.4. Materials 39
4.2.4.1. Clinical questionnaires 39

4.2.4.2. Emotion regulation training 39
4.2.5. Design 40
4.3. Results 42
4.3.1. Temporal Order Memory 42
4.3.2. Temporal Distance Judgments 42
4.3.3. The Relationship Between Individual Differences and Retro-segmentation 45
4.4. Discussion 45

5. GENERAL DISCUSSION **48**

BIBLIOGRAPHY **51**

APPENDIX A **61**
A.1. Part 1: Underlying Mechanisms of Event Segmentation 61
A.1.1. Experiment 1 61
A.1.2. Experiment 2 61
A.1.3. Comparison between Experiments 1 & 2 62
A.1.4. Experiment 3 62
A.1.5. Experiment 4 63

APPENDIX B **67**
B.1. Part 2: Online Effects of Reward on Event Segmentation 67
B.1.1. Experiment 1 67
B.1.2. Experiment 2 68

APPENDIX C **69**
C.1. Part 3: Retrospective Effects of Emotion Regulation on Event Segmentation 69

LIST OF FIGURES

Figure 2.1. Design for experiments 15
Figure 2.2. (A and B) Temporal order accuracy and (C and D) temporal distance judgments for within-event and across-event items for Experiment 1 and Experiment 2. 18
Figure 2.3. Temporal order memory accuracy difference between within and across items for Experiments 1 and 2. 19
Figure 2.4. Temporal order memory and temporal distance judgments for Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions. 20
Figure 2.5. Temporal order memory and temporal distance judgments for Experiment 4. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions. 21

Figure 3.1. Design for experiments 28
Figure 3.2. Segmentation score (difference value) for temporal order memory for Experiment 1 and 2. 31
Figure 3.3. Segmentation score (difference value) for temporal distance judgments for Experiment 1 and 2. 31

Figure 4.1. Design for experiment 43
Figure 4.2. Temporal order memory accuracy and temporal distance judgments across conditions and for each pair type 44
Figure 4.3. Temporal order memory accuracy and temporal distance judgments across conditions and for each pair type 44

Figure A.1. Temporal order memory RTs for within and across-event pairs in Experiment 1 and Experiment 2. 63
Figure A.2. Temporal order memory confidence judgments for within and across-event pairs in Experiment 1 and Experiment 2. 64

Figure A.3. RTs for temporal distance judgments for within and across-event pairs in Experiment 1 and Experiment 2. 64
Figure A.4. Confidence judgments for temporal distance judgments for within and across-event pairs in Experiment 1 and Experiment 2. 64
Figure A.5. Temporal order memory accuracy for within and across-event pairs between Experiments 1 and 2. 65
Figure A.6. Temporal order memory accuracy for within and across-event pairs between conditions for Experiment 3. 65
Figure A.7. Temporal order memory RTs for prediction error and contextual stability blocks in Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions. 65
Figure A.8. Temporal order memory confidence judgments for prediction error and contextual stability blocks in Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions. 66
Figure C.1. Correlation matrix for individual difference measures and segmentation scores. 70

1. GENERAL INTRODUCTION

Episodic memory is essential for human life as it holds the "summary records of past experiences" (Conway 2009). As time inevitably moves forward, episodic memory plays a crucial role in encoding, storing, and later retrieving experiences, enabling individuals to become consciously aware of their past under specific conditions and at a particular time (Tulving 1993). By this property, episodic memory has a distinct ability to allow humans to mentally time-travel through their experiences. This process is supported by autonoetic awareness, which is defined as a process that enables us to access the subjective timeline of past events mentally (Tulving 2002). Thanks to these, a person can remember the past, recall specific information in a given moment, and imagine future scenarios.

Different properties of episodic memory were defined to clarify its characteristics (Conway 2009). Episodic memories are richly detailed representations of past experiences that integrate sensory, perceptual, conceptual, and emotional information and are often encoded as vivid, image-like mental representations. They carry a distinct spatial perspective, either from the original point of view or as an outside observer. When recalled, episodic memories are accompanied by a subjective sense of re-experiencing and play a central role in autobiographical memory. Despite their specificity, they are highly susceptible to forgetting as well. Lastly, they are anchored in a specific temporal context, reflecting brief slices of experience typically ordered in time as they occurred.

To understand how episodic memories are temporally organized, one essential process to consider is event segmentation. It refers to the process of mentally parsing continuous experience into discrete, meaningful memory units. Even though we perceive the world as a continuous stream of experiences, memories are chunked into discrete units, such as remembering the time spent at work and commuting back home as two separate events: a work event and a commute event. Event segmentation plays a significant role in forming episodic memories (DuBrow and Davachi 2013; Ezzyat and Davachi 2011), generating future thinking (Demblon and

D'Argembeau 2014), and making predictions about upcoming events (Bilkey and Jensen 2021) by structuring memories into meaningful and retrievable memory bits (Zacks et al. 2007).

1.1 Theories of Event Segmentation

Different theories aim to explain the mechanisms underlying event segmentation. Among these, the most influential is the Event Segmentation Theory (EST; Zacks et al. 2007). According to EST, observers form cognitive representations that enable them to perceive ongoing experiences in a dynamic world. These representations, maintained in working memory, are called event models. EST posits that perception is not continuous; rather, the perceptual system interprets events through predictions and expectations about what is likely to happen next (Zacks 2019). Within this framework, it is proposed that event segmentation occurs when there is a perceptual or conceptual mismatch between incoming information and the predictions generated by the current event model. This mismatch is known as a prediction error. For instance, an observer may form an event model centered on the goal of preparing a meal, but this model is replaced when an unexpected message arrives that requires an immediate response. In this case, the observer must update the existing event model in working memory to reflect the new circumstances (Nolden et al. 2024). In sum, prediction errors emerge when expectations based on the current event model do not align with real-world input. These errors play a crucial role in the structure and formation of events, as they trigger the updating of event models and the segmentation of experiences.

An alternative theory suggests that event segmentation is not triggered by only prediction errors but also internally generated inferences and motivations (DuBrow and Davachi 2016; Shin and DuBrow 2021). In this view, segmentation arises when there is a mismatch between inferred expectations and incoming information, shifting the emphasis away from low-level sensory processing. Such transitions can reflect contextual shifts that are shaped by either external cues or internal cognitive processes. Supporting this perspective, studies have shown that segmentation occurs when participants voluntarily switch between task rules based on their motivations, rather than being externally instructed (Wang and Egner 2022). Furthermore, segmentation does not emerge when prediction errors are triggered in the absence of contextual stability following a transition (Güler et al. 2025).

Another theory, the structured event memory (SEM) (Franklin et al. 2020), claims that Bayesian statistical learning and latent structure inferences are the main driving factors in generating segmented memories. Humans learn predictable scene dynamics through experience and represent these experiences as schematic patterns to regulate noisy environmental information, improve recall, and support generalization. Events are evaluated as latent components that generate segmented experiences over time. Accordingly, the model emphasizes relational and temporal aspects of events and offers a flexible understanding of scaling the natural input in episodic memory. Even though SEM suggests that boundaries are triggered by prediction error, it focuses more on statistical comparison between the current event structure and the experiences. If the experience does not belong to the current event structure, then the occurrence of a new event is triggered.

Lastly, the event horizon model (EHM) (Radvansky 2012; Radvansky and Zacks 2014) explains the occurrence of event segmentation by offering a causal structure of experiences and how people use this structure to assist memory retrieval. When multiple associated events are available, recall of a memory can be interrupted, and the reverse pattern is observed when recall depends on a single event. This perspective is also highly associated with representing current experiences in working memory because it assists in accessing related memories by holding the current event model active. Therefore, recalling experiences from across events would be difficult since they rely on different event models.

1.2 What Influences Event Segmentation, and How Does It Affect Episodic Memory

Event segmentation typically occurs at boundaries that are determined by salient physical changes during continuous perceptual activity (Butz et al. 2021), such as changes in object categories (DuBrow and Davachi 2016), background colors (Heusser et al. 2018), and motion features (Schubotz et al. 2012). For example, transitioning from one object category to another during learning is typically interpreted as a contextual shift, leading individuals to perceive it as the onset of a new event (Güler et al. 2024, 2025). Moreover, event boundaries are influenced by our interactions with the external world, as boundaries form when our predictions are not met regarding stimulus categories (Clewett and Davachi 2017; Zacks et al. 2011; Zacks and Swallow 2007), learned regularities (Hard et al. 2019), goal-directed actions (Huff et al. 2012), temporal order (Schapiro et al. 2013; van de Ven et al. 2021), or task rules (Wang and Egner 2022). In line with the role of external factors in event segmentation, event boundaries overlap across individuals (Baldassano et al. 2018; Chen et al. 2017; Speer et al. 2003; Zacks 2019).

The transition between events influences the formation of episodic memory in terms of temporal and source memory (Clewett et al. 2020; Clewett and Davachi 2017). One of the most consistent findings supporting event segmentation is that temporal order memory indicates higher accuracy for items within the same event compared to items that span an event boundary, referred to as within-event and across-event items, respectively. Another commonly observed effect is subjective temporal distance, whereby items within an event are perceived as temporally closer than items that cross an event boundary. Notably, these effects emerge when the objective temporal distance between item pairs is held constant, suggesting that the presence of an event boundary disrupts sequential encoding and alters the perceived temporal structure of experience (DuBrow and Davachi 2014, 2016; Pu et al. 2022). Moreover, attentional resources tend to increase at event boundaries to facilitate the processing of novel information and the transition between events. This heightened allocation of attention is associated with enhanced source memory and recall for boundary items and those presented in close temporal proximity (Heusser et al. 2018; Gold et al. 2017; Pradhan and Kumar 2022). Therefore, event segmentation allows temporal, spatial, or goal-directed discontinuities in experience to be marked, enabling the organization and sequencing of episodic memories.

1.3 Underlying Neural Mechanisms of Event Segmentation

The event segmentation phenomenon is supported by neuroimaging studies (Baldassano et al. 2017; Sols et al. 2017; Speer et al. 2007). fMRI and electrocorticography studies have shown that the hippocampus tends to encode information, particularly at event boundaries (Baldassano et al. 2017; Ben-Yakov et al. 2013; Liu et al. 2022; Michelmann et al. 2021). These boundary-related signals are thought to support the formation of discrete memory traces, as the hippocampus plays a role in temporal integration by updating contextual representations when prediction errors or perceptual changes occur. Beyond the hippocampus, regions such as the posterior medial cortex and medial prefrontal cortex have also been implicated in processing event boundaries and supporting narrative comprehension and memory integration (Zacks et al. 2001; Reagh et al. 2020). Together, these findings suggest that event segmentation relies on a distributed network that monitors contextual shifts and supports the reorganization of ongoing experience into meaningful memory units.

1.4 Part 1. Underlying Mechanisms of Event Segmentation: Prediction Error vs Contextual Stability

The underlying mechanism for perceiving these event boundaries remains a central theoretical question. Two prominent accounts propose distinct mechanisms. While one of them emphasizes the prediction error as an underlying factor, the alternative suggests the stability of the context. Even though studies are confirming the contributions from both accounts, the clear distinction between them has not been tested. Accordingly, in Part 1, prediction error will be used as a mismatch between the expected likelihood of an event transition and its actual occurrence. On the other hand, the concept of contextual stability will be used to refer to the sustained presence of an internal or external context, such as perceptual features or internal goal inferences, over a period of time.

The event segmentation theory (EST) emphasizes prediction error, the detection of mismatches between expected and actual event representation, as a trigger for segmentation. Event boundaries are often characterized by increased uncertainty due to carrying information about multiple potential outcomes or actions following a transition, thereby increasing the cognitive conflict. Accordingly, prediction errors arise at event boundaries because the current event model no longer supports accurate anticipation of upcoming events (Kurby and Zacks 2008). These momentary errors are cues for the cognitive system to update or replace the existing model. When individuals detect the onset of a new event, this internal conflict is typically resolved or diminished, indicating a shift to a newly selected event model.

An alternative view highlights the role of contextual stability, where changes in perceptual, semantic, or affective context occur, prompting a new event to be inferred (Clewett and McClay 2024; DuBrow and Davachi 2016; Loh et al. 2016; Wang and Egner 2022). Accordingly, the emergence of a new event model can also be defined by predictable transitions, such as shifts in motivations, goals, or expected perceptual changes. What is critical at this point is the change in the existing context, regardless of its predictability.

While both mechanisms have received empirical support, the relative contributions of each and whether one of them is a more prominent factor remain unclear. Accordingly, in Part 1, we aimed to disentangle these mechanisms by independently manipulating prediction error and contextual stability across 4 experiments, allowing us to assess their distinct and potentially interactive effects on event segmentation.

1.5 Part 2. Online Effects of Reward on Event Segmentation

People tend to prioritize information that is associated with reward, and in doing so, may fundamentally reshape how memories are structured and organized over time. Think back to a vacation you've taken. You may have visited several cafés, shops, and museums, some memorable, and others forgettable. Over time, you might realize that the moments you remember most clearly tend to come from a specific type of experience. In this case, all the local food spots you discovered unexpectedly and loved. Even if you can't recall every single dish, the category of "local food discoveries" becomes more vivid in your memory and stands out from the rest of the trip in your memories. This suggests that our brains may prioritize and segment experiences not just based on individual events, but also on the reward value associated with broader categories.

Effects of online reward associations are also observable in various cognitive processes that are closely linked to event segmentation. For instance, visual working memory performance can be enhanced, and reward-associated items can be better maintained, regardless of their perceptual salience (Gong and Li 2014). Additionally, attentional processes can be modulated and increased by reward expectations associated with stimuli held in working memory (Infanti et al. 2015). Moreover, such prioritization during online encoding has resulted in stronger long-term memory representations for these items (Sandry et al. 2020). Given these findings, it becomes crucial to understand how the structure of memory and event segmentation may dynamically change when reward-related information is introduced during online learning.

Although reward has been widely studied in relation to attention and memory, relatively few studies have directly examined its influence on event segmentation. Reward-related associations may act as meaningful boundaries, leading to the segmentation of ongoing experience into discrete memory episodes. For instance, Rouhani et al. (2020) demonstrated that unexpected changes in reward value (reward prediction errors) can generate boundaries, resulting in better recall for information that follows such events. Similarly, surprising or motivationally salient outcomes can restructure the experience flow and generate distinct memory segments (Kalbe and Schwabe 2022). While these findings imply a link between reward associations and event segmentation, more research is needed to understand how abstract or category-level reward associations, rather than trial-by-trial surprises, may shape the structure of episodic memory during ongoing learning.

To address this gap, Part 2 investigated whether online category-level reward associations influence how people segment and encode unfolding experiences. Specifically, we tested whether high-reward categories are more likely to be treated as boundaries in ongoing experience, thereby altering the structure of episodic memory during encoding and later retrieval.

1.6 Part 3. Retrospective Effects of Emotion Regulation on Event Segmentation

Beyond perceptual processing, event segmentation is increasingly recognized as being sensitive to top-down influences. Affective and motivational states, in particular, can shape how experience is structured in memory both as it unfolds and in retrospect. How we learn to associate value with certain categories or meanings and how that value reshapes the way we mentally organize our past can determine the structuring of experiences and how we interpret them later. For example, imagine having an argument with your partner. In the moment, the experience might naturally divide into “before the fight” and “after the fight.” But perhaps hours or even a day afterward, you reflect on the event and come to realize that you may have been at fault. This new understanding does not just update your beliefs; it can lead you to re-segment the memory retrospectively.

Such cases highlight the dynamic nature of memory and suggest that event segmentation is not a fixed process, but one that can be flexibly restructured by later emotional or inferential insights. Emotional transitions, especially those involving shifts in arousal, valence, or motivational relevance, may operate as internal boundaries, segmenting experience and altering how surrounding information is encoded. For instance, memory can be retrospectively prioritized for neutral items temporally close to the rewarded items (Braun et al. 2018). In that sense, memory for events can be modified retrospectively through processes such as reinterpretation, emotion regulation, or the emergence of new goals. These observations raise important questions about the flexibility of event boundaries and the extent to which segmentation is subject to ongoing cognitive control.

Building on this idea, Part 3 investigates whether event structure can be altered retrospectively through cognitive reappraisal. Specifically, we examined how the memory representations of negative high-arousal stimuli change when those stimuli are later reinterpreted through reappraisal. By comparing conditions in which cognitive reappraisal was applied, negative experience was only reconsidered or when none of them applied, we aimed to test whether altering the emotional meaning of previously encoded events leads to changes in their segmentation and organization in memory. This approach allows us to assess how top-down emotional regulation may reshape the boundaries of past experiences and influence how they are reconstructed over time.

1.7 General Aim

The present thesis investigates these questions across three lines of inquiry. First, it contrasts prediction error with contextual stability as candidate mechanisms for driving segmentation, aiming to isolate their unique and interactive effects. Second, it examines how moment-to-moment changes in reward associations influence segmentation during encoding. Finally, it explores whether retrospective emotional regulation, specifically cognitive reappraisal of negative experiences, can reshape the structure of previously encoded events. Together, these studies aim to clarify how cognitive, affective, and motivational signals jointly determine how events are parsed and represented in episodic memory.

2. PART 1: UNDERLYING MECHANISMS OF EVENT SEGMENTATION

2.1 Introduction

Imagine walking on the beach and continuing your walk in the city. While the initial experience feels continuous, your memory will likely be segmented into distinct beach and city events. This process, known as event segmentation, involves parsing continuous experiences into discrete units in episodic memory (Zacks 2019). It influences how we encode and remember experiences (Davachi and DuBrow 2015; Heusser et al. 2018; Wu et al. 2023), making our memories easier to navigate (Michelmann et al. 2023).

Although the factors that generate distinct events are well studied, developing a global theory that involves these factors has been challenging. The dominant view is that event segmentation occurs due to prediction errors. According to the event segmentation theory, a prediction error signals the memory to create a new event (Rouhani et al. 2020; Zacks et al. 2009; Zacks and Swallow 2007). Following a prediction error, the observer forms a representation of what is happening now, called an event model, to predict the future and compare this model to the ongoing experience (Bailey et al. 2013). This theory was supported by studies that found violations of predictions result in event segmentation, as seen in cases of unexpected changes in narratives, background colors, or object movements (Eisenberg et al. 2018; Heusser et al. 2018; Reynolds et al. 2007; Zacks 2004; Zacks et al. 2011; Zacks and Tversky 2001).

While event segmentation theory remains dominant, an alternative perspective, the contextual stability account, offers a different explanation. This account suggests that what drives segmentation is a transition across stable contexts, such as a change in object categories, task rules, or reward values (DuBrow and Davachi 2016; Loh et al. 2016; Wang and Egner 2022; Yates et al. 2023). Consistent with this, contextual overlap is critical for indices of segmented memories, such as coherent temporal encoding of events (Qiu et al. 2023; Schapiro et al. 2013; Sherman et al. 2023) and strong associations among items and sources (Polyn et al. 2009; Rouhani et al. 2023; Siefke et al. 2019). Moreover, an fMRI study showed that items within a context exhibit higher hippocampal pattern similarity than items across different contexts, with this enhanced similarity predicting smaller perceived temporal distances between within-context items, a key metric for segmented memories (Ezzyat and Davachi 2014). Notably, even anticipated transitions and voluntary task switches, which are presumably free from prediction errors, have been shown to cause segmented memories (Pettijohn and Radvansky 2016; Shim et al. 2024; Wang and Egner 2022). Together, these studies suggest that having stable contexts, rather than experiencing prediction errors, is the main driver of segmentation.

Although these two views have been described in detail (Shin and DuBrow 2021; Zacks et al. 2011; Zacks and Swallow 2007), a conclusive comparison of their contributions to event segmentation has yet to be achieved. This gap may stem from the inherent challenge of dissociating these two views, as transitions in context have been suggested to produce prediction errors (Greve et al. 2017; Grisoni et al. 2021; Kim et al. 2014; Yazin et al. 2021). Consequently, effects typically attributed to prediction errors might also reflect shifts across stable contexts. For example, moving from one room to another while carrying virtual objects results in poorer memory performance for objects across rooms than objects from the same room (Radvansky et al. 2011; Radvansky and Copeland 2006). This poorer performance can be interpreted in two ways: one perspective attributes it to prediction errors triggered by perceptual changes, while the other considers it the consequence of a shift from one stable context to another (Wang and Egner 2022; Zacks et al. 2011).

Here, we developed an experimental procedure to overcome the challenge of disentangling the contributions of prediction errors and contextual changes in event segmentation by keeping prediction errors constant while manipulating contextual stability (Experiments 1-3) and keeping contextual stability constant while manipulating prediction errors (Experiment 4). Participants viewed images of real-life objects of various categories, and performed different task that provided different associated reward values (DuBrow and Davachi 2016; Ezzyat and Davachi 2014; Wang and Egner 2022; Wen and Egner 2022). In all experiments, violations of expectations regarding the upcoming object category, task rule, and reward value were considered prediction errors, such as when a series of a particular task rule was interrupted by another. Experiments 1-3 manipulated contextual stability by either having the same object category, task rule, or reward value across a series of successive items (prediction error + stable context) or having a deviant item interspersed across others (prediction error only). In Experiment 4, we kept contextual stability constant and manipulated prediction errors by providing a counter for the remaining number of items in an object category and task rule. Thus, a prediction error regarding a transition in object category or task rule was present only in the absence of a counter. In all experiments, after a brief intervening task that aimed to prevent rehearsal, participants completed temporal order and temporal distance tasks commonly used to assess event segmentation (Clewett et al. 2019; DuBrow and Davachi 2013; Rouhani et al. 2020; Sols et al. 2017; Wang and Egner 2022).

2.2 Methods

2.2.1 Ethical Approval

The study was conducted at Sabancı University, Istanbul, Turkey. The experiments of the study were approved by the Sabancı University Research Ethics Council (SUREC) and were in line with the principles of the Declaration of Helsinki (World Medical Organization 1964).

2.2.2 Open Science Practices

The experiments reported in this article were not preregistered. Analysis script, raw data files, and code for the experiments are available on the Open Science Framework repository (https://osf.io/zasmy/).

2.2.3 Participants

Before conducting the study, we ran a statistical power analysis using Bayesian sequential design. We averaged the effect sizes across six studies that primarily measured event segmentation through temporal judgment tasks (D'Argembeau et al. 2015; Heusser et al. 2018; Horner et al. 2016; Sols et al. 2017; Van De Ven et al. 2022; Wang and Egner 2022). We used an uninformed Cauchy distribution as the prior. For Experiments 1 and 2, the minimum and maximum number of participants were determined as 40 and 126, with a maximum power of .68 and a minimum power of .37 (false positive rate: .02), respectively. For Experiments 3 and 4, we ran the power analysis by considering the effect sizes of the within-subject design studies (Clewett et al. 2020; DuBrow and Davachi 2013; Heusser et al. 2018; Horner et al. 2016; Sols et al. 2017; Van De Ven et al. 2022; Wang and Egner 2022; Wen and Egner 2022), and the minimum and maximum number of participants were determined as 53 and 240, with a maximum power of .57 and a minimum power of .40 (false positive rate: .02), respectively.

For Experiments 1 and 2, we ran 42 participants and data from 2 participants were removed from further analyses due to being more than 2.5 standard deviations above or below the grand average in any of the measures. The main analyses were carried out with 40 participants in each experiment (Experiment 1: 29 female, Mage = 22.8, SDage = 3.29; Experiment 2: 32 female, Mage = 22.5, SDage = 2.21). For Experiment 3, we collected data from 63 participants. Data were removed from 6 participants due to the experiment crashing when participants pressed an invalid key, producing incomplete data and from 4 participants for being 2.5 standard deviations above or below the grand average in any of the measures. The analyses were conducted with 53 participants (29 male, Mage = 22.8, SDage = 2.79). For Experiment 4, we initially collected data from 53 participants but did not observe event segmentation. To eliminate the possible explanation of fatigue, we conducted the same experiment with 12 rounds, as in previous studies (Heusser et al. 2018; Van De Ven et al. 2022) and collected data from 23 participants. During the data collection process, we spotted a mistake in the analysis code, the correction of which resulted in robust event segmentation both in the older 16-round version and the newer 12-round version (excluding 2 practice blocks from each condition). Therefore, we combined the data across these two versions, adding up to 76 participants in total. 6 participants were removed for being 2.5 standard deviations above or below the grand average in any of the measures. The analyses were conducted with the remaining 70 participants (25 male, Mage = 22.2, SDage = 2.76).

2.2.4 Stimuli

A collection of 721 photographs of real-life objects, animals, and plants were used as memory items for Experiments 1 and 2, while a total of 910 animate and inanimate photographs were used for Experiments 3 and 4 (available in the OSF repository). We rescaled these photographs to have comparable pixel counts (500x500 pixels; 12.2° wide). The experiment was programmed in MATLAB via the Psychophysics Toolbox (Brainard 1997; Pelli 1997; Kleiner et al. 2007). The viewing distance was 65 cm from the screen. The background was gray (RGB = [127.5 127.5 127.5]).

2.2.5 Design

The experimental procedure for the experiments is shown in Figure 2.1. Each round consisted of three phases: encoding, filler task, and memory test. Experiments 1 and 2 took 75 minutes, and Experiment 3 and 4 took 90 minutes.

During encoding, participants evaluated the objects according to a task rule by using right or left arrow keys. Each response (e.g., like or dislike) was associated with one side of the screen and, therefore, one arrow key (i.e., left or right). Images did not repeat in the experiment and their assignment to conditions was counterbalanced across participants. The display duration for objects was 2500 ms with a 2000 ms inter-stimulus interval (ISI).

2.2.5.1 Experiment 1

Experiments 1 and 2 included 12 blocks, including one practice block. In Experiment 1, 30 items in each block came from three different object categories (real-life objects, animals, plants). One of the categories will be referred to as the critical category, and the other two as non-critical categories. Items from the critical category were evaluated with a different rule (e.g., bigger or smaller than a shoebox) than the non-critical categories (e.g., natural or manmade). Moreover, the critical category provided reward, while the non-critical categories provided no reward. The goal of switching the object category, task rule, and reward at ‘boundaries’ was to increase the chances of segmentation. The critical category appeared in every six items (boundary items), and within-event items were from non-critical categories. Within-event image categories were equally chosen from non-critical categories and appeared in random order to ensure that each block had an equal number of non-critical categories. The task rule was shown on the screen during both the ISI and the object display. Images from the critical category were used to explore event boundaries. Participants were informed that they would evaluate the critical category items with a different rule and get a reward value for their judgments.

After encoding 30 images, participants performed basic mental summation for 45 seconds as a filler task (Wang and Egner 2022). After the filler task, participants received the memory tests. During the memory test phase, participants were given 8 image pairs that they encoded during the encoding phase. Half the pairs were within, and the other half were across-event items. The temporal distance was equal for each pair, as there were always two images between the tested pairs. For each image pair, participants first made temporal order judgments by indicating which item came first during encoding using left and right arrow keys corresponding to the pair items' positions on the screen. The positions of the pair items were randomly shuffled for each tested pair. Next, participants made temporal distance judgments for the same image pair among four options (very far, far, close, very close) by assessing the temporal distance between images during encoding. Participants were also asked to indicate their level of confidence in their temporal order and temporal distance judgments (high or low confidence). Reaction time, confidence judgment, and accuracy were recorded.

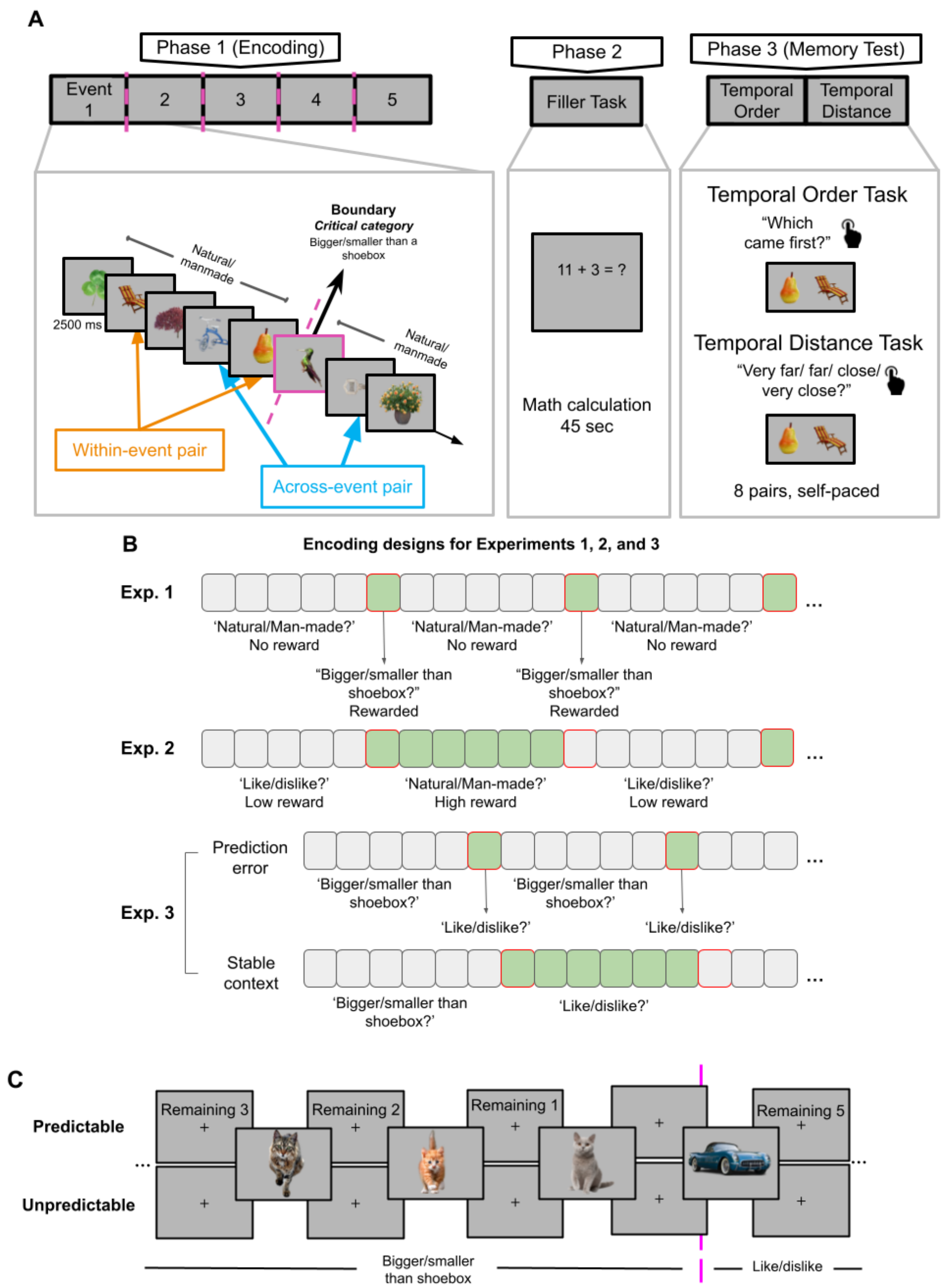
2.2.5.2 Experiment 2

Experiment 2 was the same as Experiment 1 except for the following differences in Phase 1. First, participants evaluated every six consecutive items with the same rule (e.g., like/dislike) and the same reward value (e.g., high reward). In other words, task and reward values changed after every six items. Therefore, there was contextual stability during these items. Second, there was no critical category, as boundaries were determined via the stability of the task rule and reward value across six consecutive items.

2.2.5.3 Experiment 3

Experiment 3 was identical to Experiments 1 and 2 except for the following differences. The prediction error blocks (Experiment 1) and contextual stability blocks (Experiment 2) were combined into a single experiment as a within-subjects manipulation. There were 14 experimental blocks, 7 for prediction error and 7 for contextual stability. The block order was random except for avoiding repeating the same condition more than twice across consecutive blocks. Before the study, participants completed two practice rounds for each condition. All remaining changes aimed to simplify the design and reduce unnecessary variance in Phase 1. First, there was no reward manipulation. Second, each block had two predefined object categories (e.g., toys and flowers) instead of three, minimizing semantic relatedness and strengthening transitions. Third, instead of three rules, there were two rules throughout the experiment, which were "bigger or smaller than a shoebox" and "like or dislike". Fourth, object categories, their presentation order within and across blocks, and task rules to evaluate each object category were counterbalanced across participants and conditions. Lastly, in prediction error blocks, each event consisted of 5 items from a single object category and were evaluated with one rule,

Figure 2.1 (A) Main phases of Experiment 1. There were three phases: encoding, filler task, and memory test. At the encoding phase, participants evaluated each image with a rule. In the memory test phase, participants performed temporal order and temporal distance judgment tasks for image pairs. (B) At the encoding phase, Experiment 1 aimed to create prediction errors by including a distinct object category, task rule, and reward value every 5-6 items. Experiment 2 involved stable contexts, where the transitioned task rule and reward value persisted for 5-6 items before another change. Experiment 3 manipulated these factors as a within-subject variable without reward. (C) Experiment 4 manipulated the predictability of event transitions with a counter for the remaining objects in a given category and task rule in half of the rounds.



and the boundary items were from the other category and were evaluated with the other rule. For contextual stability blocks, each event consisted of 6 items from a single object category and were evaluated with the same rule. Thus, for both conditions, the event transitions were every 6 items to ensure equal event onsets across conditions. This revision enabled the same order-items to be asked in temporal order and temporal distance tasks in both conditions. In contrast, in Experiments 1 and 2, the offsets of events (i.e., the boundaries) were matched, not the onsets.

2.2.5.4 Experiment 4

Experiment 4 was identical to Experiment 3 except for the following changes that were introduced to manipulate prediction errors. There were two block types: In predictable blocks, a counter indicated how many items were left for the upcoming transition, which was displayed during ISI. There was no counter in unpredictable blocks (Figure 1C). There were 16 blocks, though some participants completed only 12 blocks due to a coding mistake (see Participants). The first of each block type was for practice, leaving 7 experimental blocks for each block type (and 5 for each block type in the 12-block version). The block type alternated every four blocks, and the order was randomized across participants. In each round of Phase 1, participants encoded 36 objects. Two changes were made to increase prediction errors. First, the object category repeated for either 5, 6, or 7 objects, instead of being fixed. Second, for each run, each event length occurred twice in a run in a pseudo-random order, without repetition across consecutive events (Shim et al. 2024). On the memory test (Phase 3), there were 6 item pairs: 3 within-events and 3 across-events.

2.3 Results

Analyses were conducted with JAMOVI 2.3 (2023) and the Bayesian Methods module (jsq). Bayesian paired and independent samples t-tests compared the within-subject differences for within vs. across boundary effects. Confidence judgments and RTs for each measure were reported in the supplementary material. BF10/01 values below 1 were considered as no evidence, 1-3 as anecdotal evidence, 3-6 as moderate evidence, 6-10 as substantial evidence, and larger than 10 as strong evidence for H1/H0.

2.3.1 Experiment 1: Does Prediction Error Generate Event Boundaries?

For temporal order memory, accuracy was higher for within-event pairs (M = .68, SD = .11) than across-event pairs (M = .64, SD = .10), with anecdotal evidence, BF10 = 1.98 (Figure 2.2.A). For temporal distance judgments, reported distance was higher for across-event pairs (M = 2.41, SD = .24) than within-event pairs (M = 2.35, SD = .22), also with anecdotal evidence, BF10 = 1.41 (Figure 2.2.C). Thus, Experiment 1 provided only anecdotal evidence for event segmentation, as reflected by higher temporal order accuracy and shorter perceived distance for within vs. across events.

2.3.2 Experiment 2: Does Contextual Stability Generate Event Boundaries?

For temporal order memory, accuracy was higher for within-event (M = .70, SD = .12) compared to across-event pairs (M = .58, SD = .12), with strong evidence, BF10 = 2050.37 (Figure 2B). For temporal distance judgments, temporal distance was higher for across-event pairs (M = 2.43, SD = .25) than within-event pairs (M = 2.32, SD = .29), with strong evidence, BF10 = 22.61 (Figure 2.2.D). Thus, in Experiment 2, we obtained strong evidence for event segmentation.

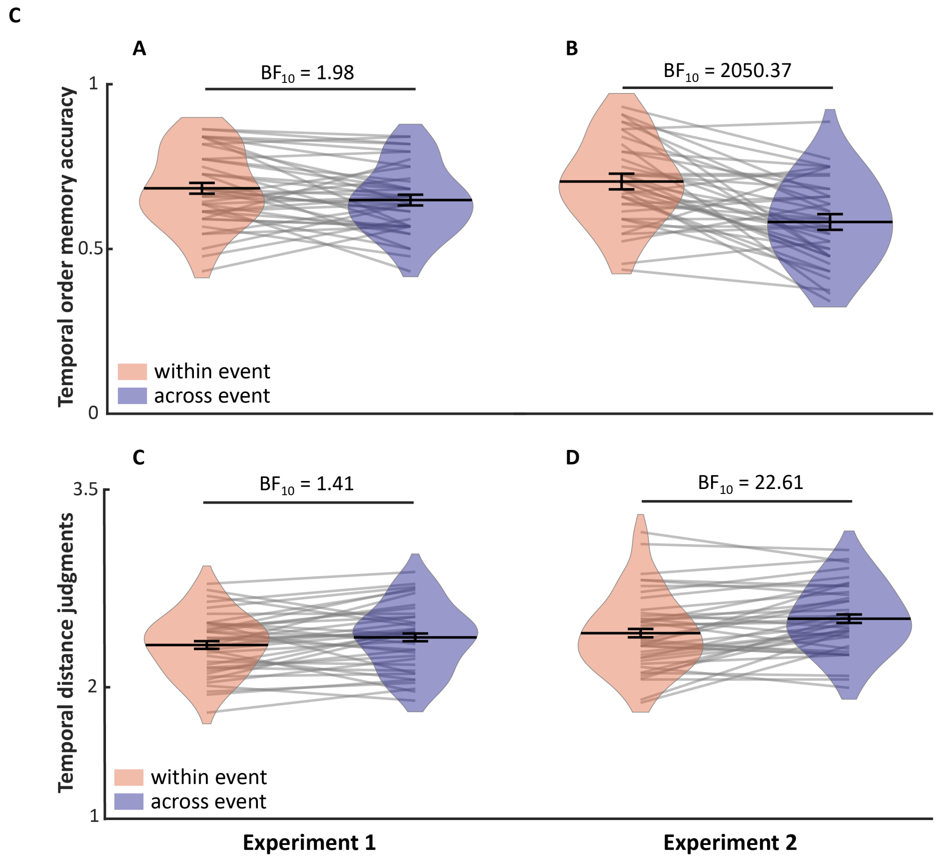
2.3.3 Between-subjects Comparison Across Experiments 1 and 2

To evaluate the contributions of contextual stability and prediction error to event segmentation, we performed between-subjects t-tests on segmentation scores across Experiments 1 and 2. Segmentation scores were calculated by subtracting the mean accuracy for across-event pairs from within-event pairs for the temporal order task. For the temporal distance task, the subtraction was reversed so that higher values consistently indicated larger segmentation. This procedure was applied to accuracy, RT, and confidence judgments for both tasks.

The segmentation score for temporal order accuracy was higher in Experiment 2 (M = .12, SD = .11) than in Experiment 1 (M = .03, SD = .10), with strong evidence, BF10 = 10.21. The segmentation score for temporal distance did not differ between Experiment 1 (M = -.05, SD = .18) and Experiment 2 (M = -.10, SD = .20), with anecdotal evidence for the null, BF01 = 1.52. These results suggest that contextual stability is more important than prediction errors in generating event boundaries

(Figure 2.3).

Figure 2.2 (A and B) Temporal order accuracy and (C and D) temporal distance judgments for within-event and across-event items for Experiment 1 and Experiment 2.



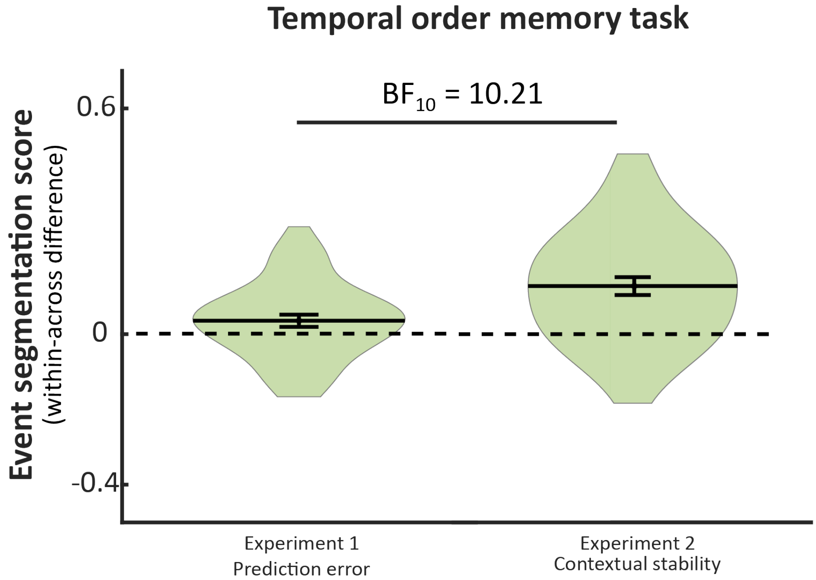
2.3.4 Experiment 3: Within-subject Replication of Experiments 1 and 2

In prediction error blocks, temporal order memory accuracy for within-event pairs (M = .64, SD = .11) was higher than across-event pairs (M = .57, SD = .07), with strong evidence, BF10 = 92.4. Similarly, in contextual stability blocks, temporal order memory accuracy was higher for within-event pairs (M = .73, SD = .12) than for across-event pairs (M = .60, SD = .11), with strong evidence, BF10 = 2.08e+7.

For temporal distance judgments in the prediction error blocks, there was no difference between within (M = 2.40, SD = .30) and across-event pairs (M = 2.43, SD = .29), with moderate evidence, BF01 = 4. In contrast, in contextual stability blocks, temporal distance was evaluated higher for across-event pairs (M = 2.40, SD = .31) than within-event pairs (M = 2.18, SD = .32), with strong evidence, BF10 = 436286.

To directly compare segmentation across conditions, we computed the difference

Figure 2.3 Temporal order memory accuracy difference between within and across items for Experiments 1 and 2.



scores (within minus across) as segmentation indices. For temporal order, segmentation was higher for contextual stability (M = .12, SD = .12) than for prediction errors (M = .07, SD = .13), with anecdotal evidence, BF10 = 2.18. For temporal distance judgments, segmentation was higher for contextual stability (M = .21, SD = .24) than prediction errors (M = .02, SD = .17), with strong evidence, BF10 = 360 (Figure 2.4).

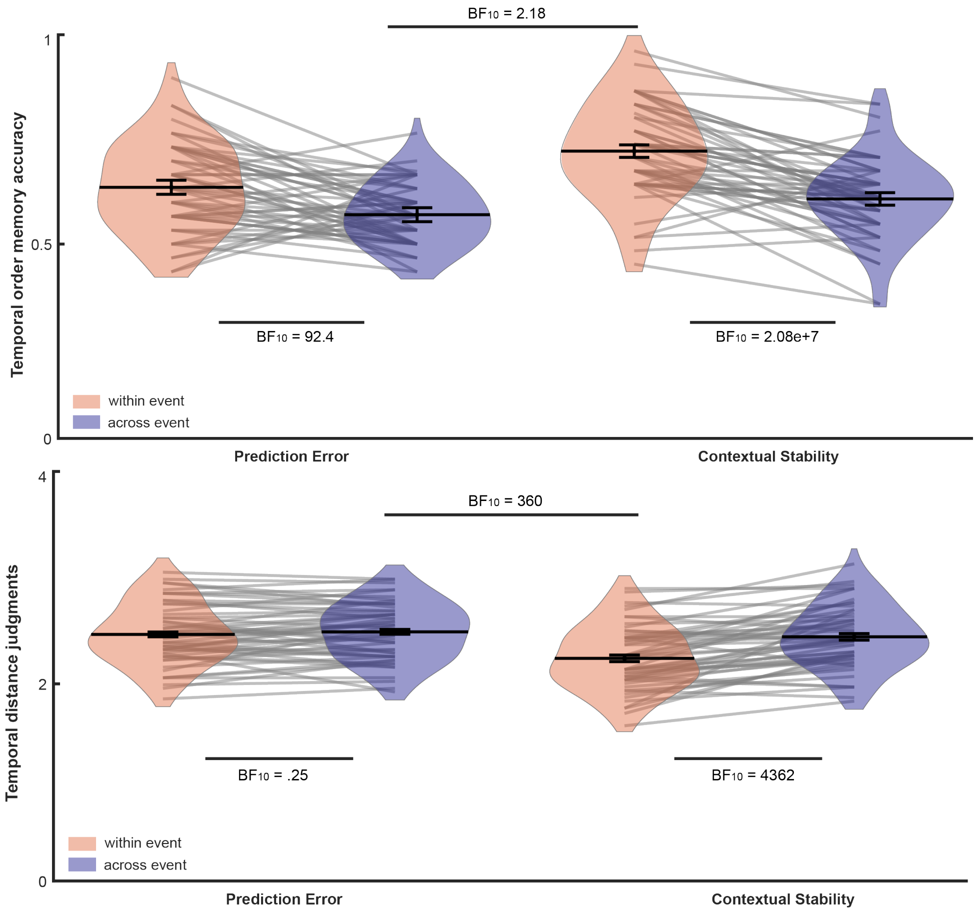
2.3.5 Experiment 4: Does Prediction Error Play a Role?

In predictable blocks, temporal order accuracy was higher for within-event pairs (M = .68, SD = .13) than for across-event pairs (M = .56, SD = .10), with strong evidence, BF10 = 1.53e+6. Similarly, in unpredictable blocks, temporal order accuracy was higher for within-event pairs (M = .67, SD = .13) than for across-event pairs (M = .56, SD = .11), with strong evidence, BF10 = 135011.

Temporal distance judgments also showed strong segmentation effects in both conditions: In predictable blocks, the evaluated distance was higher for across-event pairs (M = 2.57, SD = .33) than for within-event pairs (M = 2.24, SD = .34), with strong evidence, BF10 = 7.93e+7. Similarly, in unpredictable blocks, the evaluated distance was higher for across-event pairs (M = 2.54, SD = .32) than within-event pairs (M = 2.26, SD = .31), with strong evidence, BF10 = 1.27e+8.

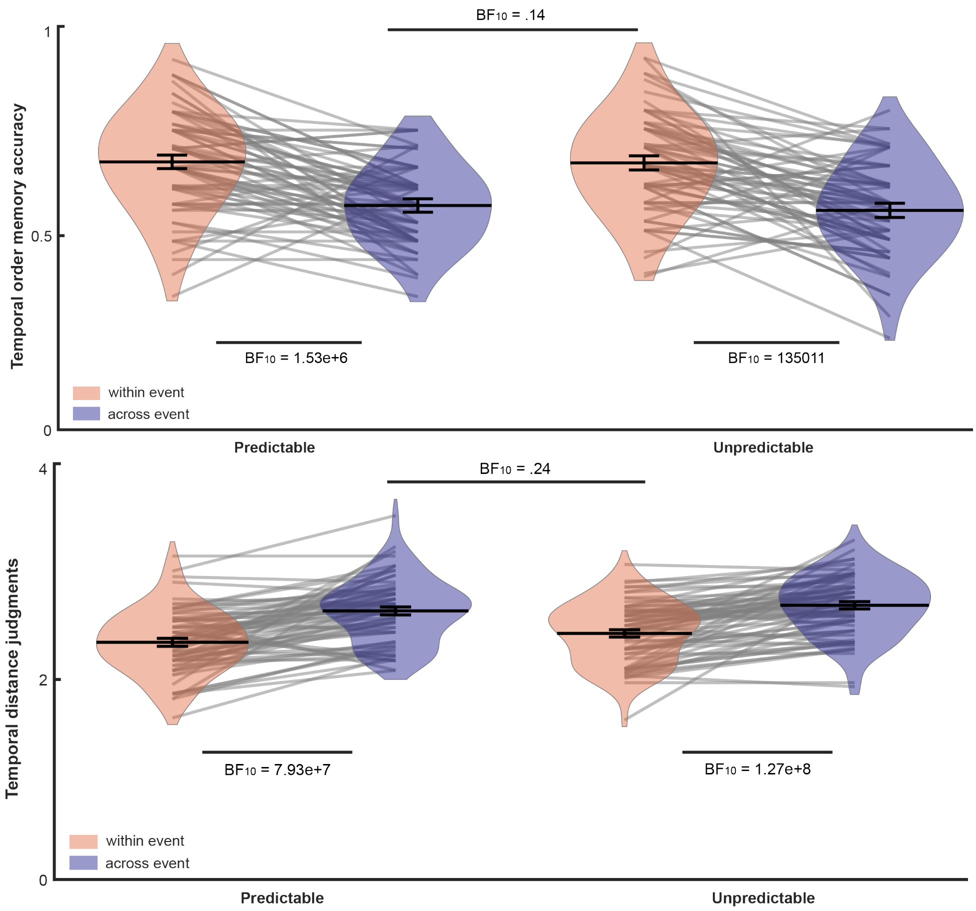
To directly compare segmentation across conditions, we computed the difference scores (within minus across) for each measure. For temporal order memory, segmen-

Figure 2.4 Temporal order memory and temporal distance judgments for Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions.



tation did not differ between predictable (M = .12, SD = .15) and unpredictable blocks (M = .11, SD = .16), with substantial evidence for the null, BF01 = 7.12. Similarly, for temporal distance, segmentation did not differ between predictable (M = .33, SD = .36) and unpredictable blocks (M = .28, SD = .30) with moderate evidence for the null, BF01 = 4.02 (Figure 2.5). Thus, there was equal segmentation across predictable and unpredictable blocks.

Figure 2.5 Temporal order memory and temporal distance judgments for Experiment 4. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions.



2.4 Discussion

We contrasted two accounts of the underlying mechanism of event segmentation. The prevailing view in the literature posits that event boundaries are shaped by prediction errors (Zacks 2004; Zacks et al. 2007). In contrast, an alternative theory proposes that transitions across stable contexts drive event boundaries (Shin and DuBrow 2021). A direct comparison of the two views has been challenging due to the difficulty of disentangling their respective influences. Here, we overcame this challenge by independently manipulating each factor across four experiments.

In Experiment 1, we introduced a transient change in object, rule, and reward categories to induce prediction errors, while in Experiment 2, the changed task rule and reward persisted for 5-6 more items during event to establish contextual stability. Segmentation was larger in Experiment 2 than in Experiment 1. We replicated this result in Experiment 3 using a within-subjects design. Observing more robust event segmentation when events have more consistent contextual information emphasizes the importance of contextual stability. However, it can be argued that contextual stability leads to higher prediction errors and, hence, better event segmentation. To address this issue, in Experiment 4, we manipulated prediction errors by providing a counter for the remaining number of items before transitions across stable contexts. Segmentation was equally robust for predictable and unpredictable transitions, revealing no effect of prediction errors. These outcomes challenge the influential event segmentation theory and instead emphasize the pivotal role of contextual stability in event segmentation.

Various aspects of contextual stability can segment events. First, having a common context can contribute to the structuring of memories by promoting associations among information within the same context and improving sequential order memory (Davachi and DuBrow 2015; DuBrow and Davachi 2016; Ezzyat and Davachi 2011; Farrell 2012; Horner et al. 2016; Pu et al. 2022; Rouhani et al. 2020; Sols et al. 2017). These associations may contribute to the segmented structure during retrieval, given the importance of context binding for episodic memory retrieval (Ezzyat and Davachi 2011; Yonelinas et al. 2019). Such associations can also assist in relating the current event with remote episodic memories that share the same context, helping to generalize from similar experiences (Hahamy et al. 2023). Second, contextual shifts may drive the removal of prior goals and task-related information from memory and their update with information appropriate for the new context. In line with this, we recently demonstrated that a context change triggers the reactivation of task-related long-term memories in working memory (Özdemir et al. 2024). This reactivation might explain how updating task-related information occurs at event boundaries.

As the field advances, it becomes crucial to clarify both the mechanisms behind segmentation and the ways different memory measures capture its components. Although prediction errors have long been considered central to event segmentation, previous findings may reflect transitions across stable contexts, as prediction errors occur at transitions in perception, reward, or semantics (Rouhani et al. 2020; Speer et al. 2004; Zacks 2004). Given the overlap of contextual shifts and prediction errors during encoding, future studies should exercise caution while interpreting the contributions of each to memory structuring. An open question for future research is to reveal which of the two is critical for triggering an event boundary: the contextual change itself or its stability after a transition.

Moreover, identifying what drives segmentation is closely tied to how it is measured, as different memory tasks may capture distinct facets of the same underlying process. We found the segmentation difference for temporal order memory between Experiments 1 and 2, while the condition difference was more robust for temporal distance judgments in Experiment 3. These differences across experiments may be attributable to noise, or they may also reflect different underlying memory processes tapped by the two tasks (DuBrow and Davachi 2014; Pu et al. 2022; Wang and Egner 2022), which can be evaluated by future studies.

Despite the contributions of the current study, two limitations can be addressed. First, in Experiment 4, participants may have noticed that transitions consistently occurred every 5 to 7 items in the unpredictable condition. This regularity could have provided some predictability, thereby reducing the degree of prediction errors (Greve et al. 2017, 2019; Van Kesteren et al. 2012). Such a reduction may partly explain the absence of segmentation difference between conditions. Nevertheless, the presence of strong event segmentation in the predictable condition, where prediction errors were minimized, provides compelling evidence that contextual stability is the primary factor for segmentation. Second, while our findings suggest that prediction errors, as operationalized in our paradigm, are not sufficient to induce segmentation without contextual stability, different types of prediction errors may still contribute to segmentation. For example, a recent study demonstrated that a single highly negative arousing image embedded within a sequence of neutral stimuli was sufficient to trigger segmentation (Harris et al. 2025). Thus, strong prediction errors involving survival-related information, such as threat signals, may be sufficient to segment episodic memories. However, since the arousing stimulus occurred in a fixed, predictable position, segmentation in that study may have been driven by arousal itself rather than by prediction error per se.

We would like to clarify that we are not arguing more broadly against the influence of prediction errors on memory. Although our findings show that prediction errors are insufficient to drive event segmentation in the absence of stable contexts, prediction errors play a well-established role in various memory-related processes (Loock et al. 2025; Pupillo et al. 2023; Ortiz-Tudela et al. 2024). For example, prediction errors have been shown to enhance memory encoding without generating segmentation (Wang and Egner 2023) by increasing attention to unexpected stimuli (Greve et al. 2017), and to support memory updating by facilitating the integration of new information that violates prior expectations (Sinclair et al. 2021). Additionally, prediction errors can trigger memory reorganization, restructuring the temporal or semantic relationships among events (Bein et al. 2020; Rouhani et al. 2020; Swallow et al. 2022).

To conclude, we found that switching across stable contexts contributes to event segmentation above and beyond prediction errors. The lack of event segmentation when only prediction error but not contextual stability was present challenges the prevailing event segmentation theory that posits segmentation is driven by prediction errors. These findings underscore the need for a comprehensive understanding of event segmentation mechanisms, shedding light on how our minds organize and remember our experiences.

3. PART 2: ONLINE EFFECTS OF REWARD ON EVENT SEGMENTATION

3.1 Introduction

Our daily life experiences are segmented into distinct memory units that form the foundation of episodic memory, a process known as event segmentation. This mechanism supports the initial encoding of ongoing experience and helps to bind new information with previous memories (Sols et al. 2017). Segmented memory units are considered essential for guiding attention and perception, and for constructing a coherent episodic memory structure (Zacks and Tversky 2001). Moreover, segmentation influences nontemporal aspects of episodic memory as well, including memory for individual items and their associated source information (Clewett et al. 2019). Event segmentation is typically studied as an online process, where memory performance is examined in relation to perceptual or external cues that shape how experience is segmented during initial encoding (Güler et al. 2025; Harris et al. 2025; Wang and Egner 2022; Wen and Egner 2022).

Since segmentation helps determine which information will be encoded and how it is later retrieved, understanding the factors that modulate this process, such as reward value, is important. Beyond its potential effects on segmentation, reward has been shown to influence memory and related cognitive processes more broadly. Motivational salience and reward enhance memory consolidation, increase attention allocation, and prioritize information in memory (Miendlarzewska et al. 2016; Raymond and O'Brien 2009). Studies indicated that reward can influence both what information is prioritized in memory and how it is temporally and structurally organized. For instance, memory for neutral items was enhanced when they occurred close in time to reward-associated items (Braun et al. 2018), suggesting that motivational salience can retroactively prioritize information. These findings imply that reward-related signals enhance item-level encoding and may influence the organization of episodic memory.

Even though there are studies evaluating the role of reward-related processes on event segmentation, a clear understanding of their role is still missing. Most existing work has focused on reward prediction errors, violations of expected outcomes, as potential triggers for segmentation (Rouhani et al. 2018; Rouhani et al. 2020; Rouhani et al. 2023). These studies suggest that reward related prediction errors can function similarly to perceptual or contextual shifts in prompting new event models. While these prediction errors have been shown to enhance recognition and source memory for boundary and within event items, they impair temporal order memory across events. Notably, some of these studies have manipulated reward expectations at the category level, suggesting that learned associations can influence how ongoing experience is segmented.

However, unlike these studies, the current work does not manipulate the presence or absence of prediction errors, as it primarily focuses on how changes in reward associations influence segmentation. We examine how stable and contextually cued reward associations affect event segmentation during learning, and whether the segmentation is changing compared to less-rewarded transitions. Accordingly, participants encountered novel objects from different categories in each block, and categories did not repeat across blocks. At the beginning of each block, participants are informed whether they are in high-low or low-low contextual transitions. This setup allows us to test whether motivationally salient category changes, when paired with a higher reward context, are more likely to be segmented compared to similar transitions in a less rewarding context.

Importantly, while the category-reward associations were block-specific and not carried across the experiment, participants acquired them through experience within each block. Thus, our design offers a way to investigate whether within-block learning of value associations, in the absence of explicit prediction error, can influence segmentation by altering attentional engagement and event models. The goal of the present study is to determine whether reward value associated with contextual transitions reshapes the perceived structure of ongoing experience, compared to similar transitions in a low-reward condition.

3.2 Methods

3.2.1 Ethical Approval

The study was conducted at Sabancı University, Istanbul, Turkey. The experiments of the study were approved by the Sabancı University Research Ethics Council (SUREC) and were in line with the principles of the Declaration of Helsinki (World Medical Organization 1964).

3.2.2 Open Science Practices

The experiments reported in this article were not preregistered.

3.2.3 Participants

For Experiment 1, we collected data from 30 participants (9 male, Mage = 21.6, SDage = 4.85). Outliers were controlled by evaluating each participant being 2.5 standard deviations above or below the grand average of temporal order accuracy and temporal distance judgments. There were no outliers. All participants were included for further analysis. For Experiment 2, we collected data from 54 participants (17 male, Mage = 21.8, SDage = 1.86). 3 participants were removed due to being 2.5 standard deviations above or below the grand average of temporal order accuracy and temporal distance judgments. Analysis were conducted with 51 participants.

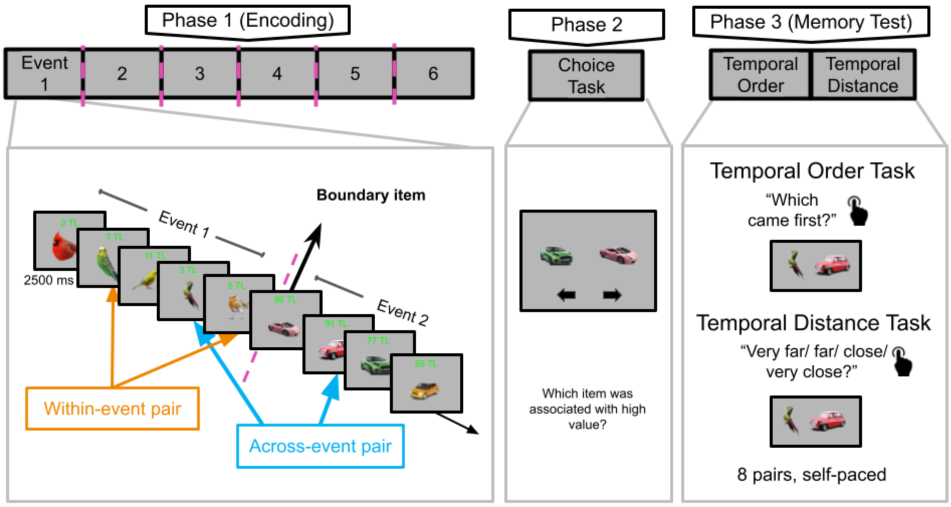
3.2.4 Stimuli

A collection of 805 photographs from various categories (e.g., cars, cats, flowers) was used as memory items in Experiment 1. For Experiment 2, an additional 569 photographs were included to create new object categories. Each image was carefully selected to be as perceptually distinct as possible. We rescaled these photographs to have comparable pixel counts (500x500 pixels; 12.2° wide). The experiment was programmed in MATLAB via the Psychophysics Toolbox (Brainard 1997; Pelli 1997; Kleiner et al. 2007). The viewing distance was 65 cm from the screen. The background was gray (RGB = [127.5 127.5 127.5]).

3.2.5 Design

The experimental procedure for the experiments is shown in Figure 3.1. Each round consisted of three phases: encoding, choice task, and memory test. The Experiments 1 and 2 took 75 minutes.

Figure 3.1 Experimental design for Experiments 1 and 2. First, participants encoded images from different object categories associated with different reward value. In figure, the phase 1 represents an exemplary high-rewarded transition. Second, they performed a choice task to indicate which item was associated with higher reward value during encoding. Lastly, they performed temporal order and temporal distance memory tasks. In experiment 2, each event consists of two object categories instead of one.



3.2.5.1 Experiment 1

There were 15 blocks, 7 for high-low and 7 for low-low reward transitions. Participants performed a practice task before moving to the main experiment. In each block, there were three phases; encoding, choice task, and memory test. During encoding, participants encoded 30 images from two different object categories (e.g., cars - cats). Each event consists of 5 images from a specific object category. Each encoding phase includes 6 events in total, 3 from each object category (e.g., AAAAA-BBBBB). Object categories were predefined to eliminate the semantic relatedness between them. The appearance of object categories were counterbalanced for each participant. Before the experiment, reward values were randomly generated for low - low and high - low transitions by using MATLAB randfixedsum function. Accordingly, min and max values and their sum were controlled for high and low reward values. For low reward blocks, participants can earn values between 1 to 20 TL during blocks. For high reward blocks, participants can earn values between 70 to 100 TL. Random reward values within these ranges were associated with each object. Participants are informed that they will get 1 percent of their total gain as a monetary reward. The total earnings were fixed at 100 TL in all cases, but participants were not informed of this and believed they could influence their earnings through their responses. During encoding, participants were passively learned the objects and their associated reward value. They were also instructed to form a narrative with the objects to help their encoding of temporal information. Object duration was 2500 ms with 2000 ISI. Images did not repeat in the experiment.

During the second phase, participants performed a choice task in which they saw two images on the screen from the just encoded sequence and asked which item was associated with higher reward value. They were also informed that their correct answers will be added to their total gain. There were 4 pairs of images in each round and were self-paced.

In the last phase, participants performed a memory test assessing their temporal order and temporal distance judgments for image pairs that they learned during encoding. There were 8 image pairs: 4 for within-event and 4 for across-event pairs. There were always 2 images between image pairs so the objective temporal distance was the same for each pair. For each image pair, participants first evaluated temporal order by indicating which item came first, and then they evaluated perceived temporal distance between them. Order information and pair type (within or across) for each pair was counterbalanced, and the questions were self-paced. They also indicated their level of confidence for each answer. RTs and accuracy were recorded.

3.2.5.2 Experiment 2

In Experiment 2, all procedures were kept identical except for one modification. Each round included images from four different categories. Each event was constructed using two object categories, and object selection was randomized such that at least two images from each category were used (e.g., ABABA – CDCDC). The object categories used in each round were unique and did not repeat throughout the experiment. To preserve semantic relatedness between categories within an event, all category pairings (e.g., cats and cars for one event, flowers and watches for another) were predetermined. This modification was introduced to reduce the transition cost associated with object category changes and to better isolate the contribution of reward changes to event segmentation.

3.3 Results

Analyses were conducted with JAMOVI 2.3 (2023) and the Bayesian Methods module (jsq). Bayesian paired samples t-tests compared the within-subject differences for within vs. across boundary effects. Confidence judgments and RTs for each measure were reported in the supplementary material. BF10/01 values below 1 were considered as no evidence, 1-3 as anecdotal evidence, 3-6 as moderate evidence, 6-10 as substantial evidence, and larger than 10 as strong evidence for H1/H0.

3.3.1 Experiment 1: Do Online Changes in Reward Value Generate a Segmentation Difference?

Temporal order accuracy was higher for within-event (M = .69, SD = .09) compared to across-event pairs (M = .61, SD = .08), with strong evidence, BF10 = 292. For high rewarded transitions, temporal order accuracy was higher for within-event (M = .69, SD = .10) compared to across-event pairs (M = .59, SD = .10), with strong evidence, BF10 = 49.8. For low rewarded transitions, temporal order accuracy was higher for within-event (M = .70, SD = .12) compared to across-event pairs (M = .62, SD = .11), with moderate evidence, BF10 = 4.37.

Temporal distance judgments were higher for across-event pairs (M = 2.48, SD = .29) than within-event pairs (M = 2.20, SD = .27) , with strong evidence, BF10 = 126784. For high rewarded transitions, distance judgments were higher for across-event pairs (M = 2.45, SD = .34) than within-event pairs (M = 2.20,SD = .28) , with strong evidence, BF10 = 650. For low rewarded transitions, distance judgments were higher for across-event pairs (M = 2.50, SD = .27) than within-event pairs (M = 2.20,SD = .29) , with strong evidence, BF10 = 67383. These results indicated the general trend of segmentation that is higher temporal order accuracy and less perceived temporal distance for within-event pairs compared to across-event pairs.

For our main interest, we compared the segmentation score between high and low rewarded transition blocks. Segmentation scores were calculated by subtracting the mean accuracy for across-event pairs from within-event pairs for the temporal order task. For the temporal distance task, the subtraction was reversed so that higher values consistently indicated larger segmentation. For temporal order memory, there was indifference between high (M = .09, SD = .13) and low rewarded transitions (M = .08, SD = .16), with moderate evidence, BF01 = 4.92 (see Figure 3.2). Similarly, for temporal distance judgments, there was indifference between high (M =

.25, SD = .28) and low rewarded transitions (M = .29, SD = .24), with moderate evidence, BF01 = 3.85 (see Figure 3.3). As a result, we were not able to observe any segmentation differences when specific information was associated with a high reward value compared to when it was linked to a low reward value.

Figure 3.2 Segmentation score (difference value) for temporal order memory for Experiment 1 and 2.

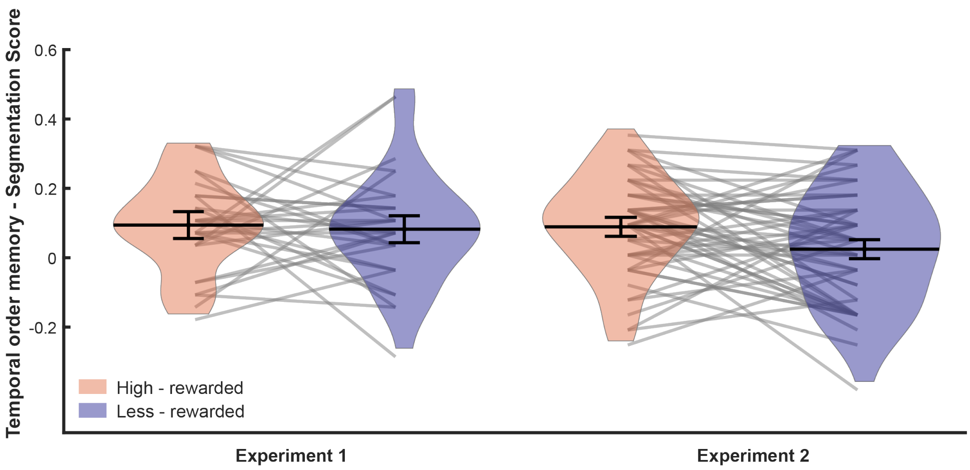
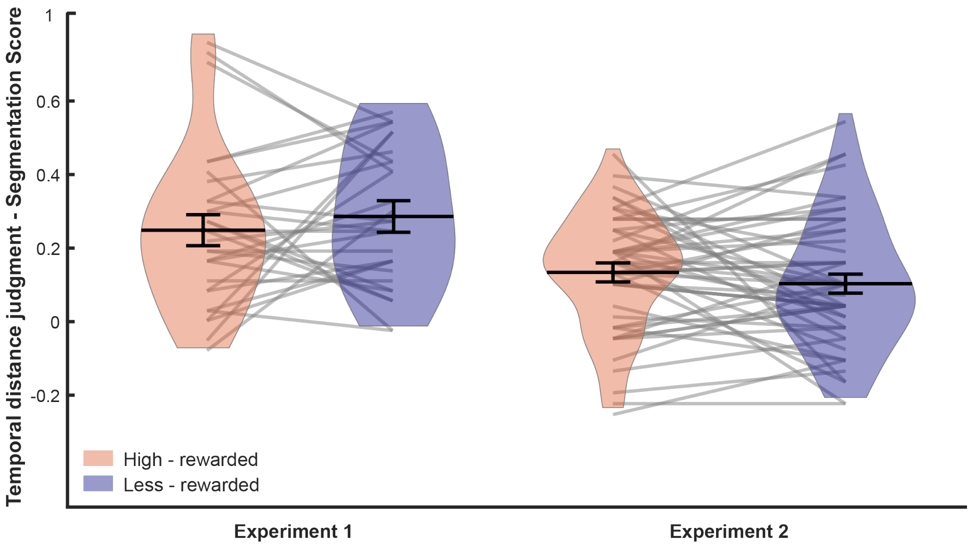


Figure 3.3 Segmentation score (difference value) for temporal distance judgments for Experiment 1 and 2.



3.3.2 Experiment 2: Does Reducing the Strength of Category Transitions Make the Effect of Reward on Segmentation More Apparent?

Temporal order accuracy was higher for within-event (M = .66, SD = .10) compared to across-event pairs (M = .58, SD = .08), with strong evidence, BF10 = 18003. For high rewarded transitions, temporal order accuracy was higher for within-event (M

= .68, SD = .11) compared to across-event pairs (M = .58, SD = .10), with strong evidence, BF10 = 16133. For low rewarded transitions, temporal order accuracy was higher for within-event (M = .64, SD = .13) compared to across-event pairs (M = .59, SD = .09), with moderate evidence, BF10 = 3.33. Temporal distance judgments were higher for across-event pairs (M = 2.44, SD = .21) than within-event pairs (M = 2.34, SD = .24) , with strong evidence, BF10 = 66. For high rewarded transitions, distance judgments were higher for across-event pairs (M = 2.42, SD = .19) than within-event pairs (M = 2.31, SD = .24) , with strong evidence, BF10 = 150. For low rewarded transitions, distance judgments were higher for across-event pairs (M = 2.45, SD = .25) than within-event pairs (M = 2.38, SD = .28) , with anecdotal evidence, BF10 = 2.10. These results indicated the general trend of segmentation that is higher temporal order accuracy and less perceived temporal distance for within-event pairs compared to across-event pairs.

For our main interest, we compared the segmentation score between high and low rewarded transition blocks. For temporal order memory, high rewarded transitions (M = .10, SD = .11) indicated higher segmentation than low rewarded transitions (M = .04, SD = .13), with anecdotal evidence, BF10 = 1.83 (see Figure 2). For temporal distance judgments, there was indifference between high (M = .11, SD = .19) and low rewarded transitions (M = .07, SD = .21), with moderate evidence, BF01 = 3.39 (see Figure 3). As a result, while temporal order memory showed a tendency toward increased segmentation following high-reward transitions, the evidence remained anecdotal. In contrast, temporal distance judgments revealed no such difference between types of reward transitions, with moderate evidence favoring the null.

3.4 Discussion

The present study investigated whether contextual reward associations influence how individuals segment ongoing experience. Across two experiments, we consistently replicated the classic segmentation effect: participants showed higher temporal order accuracy and smaller perceived temporal distances for within-event item pairs compared to across-event pairs. This pattern supports the idea that event boundaries shape the structure of episodic memory by influencing how temporal information is encoded and recalled (Clewett and Davachi 2017; Sols et al. 2017; Swallow et al. 2009; Wang and Egner 2022).

Our primary goal was to evaluate whether segmentation is further modulated by the reward value of the category transition. Specifically, we questioned whether transitions associated with high-reward contexts lead to greater segmentation than those associated with low-reward contexts. Contrary to our expectations, high-rewarded contextual transitions did not change the strength of segmentation compared to low-rewarded transitions. In Experiment 1, segmentation scores did not differ between high and low-rewarded transitions. In Experiment 2, we observed a slight increase in segmentation for high-rewarded transitions in the temporal order task, but this effect was only supported by anecdotal evidence, and it did not replicate in temporal distance judgments. Taken together, these findings suggest that the presence of motivationally salient category changes alone may not be sufficient to reshape event structure, even when the perceptual distinctiveness of category transitions is minimized to allow the effects of reward to emerge more clearly.

These results raise the possibility that event segmentation may not operate on a flexible, but instead reflects a more discrete, all-or-none process. Accordingly, when a boundary is perceived regardless of what kind of change it represents (e.g., perceptual, task-related, reward, motivation), additional modulatory signals such as reward value may have limited influence on the strength of segmentation. In other words, the presence of any salient shift (e.g., a change in object category) may be sufficient to trigger the formation of a new event model, and further enhancements, such as associated motivational value, may not amplify the segmentation effect.

While previous studies have demonstrated that emotionally or motivationally salient events can reorganize memory (Palombo and Cocquyt 2020; Talmi et al. 2019), it remains unclear whether such effects are driven by salience alone or by underlying violations of expectation. For instance, studies have shown that unexpected high arousal events can act as segmentation cues, triggering event boundaries and reorganizing temporal memory structure (Rouhani et al. 2018, 2020, 2023). However, unlike these prior studies where segmentation effects were primarily driven by violations of learned expectations, our findings suggest that motivational salience alone, when not accompanied by prediction error, may be insufficient to change the degree of segmentation.

An alternative explanation is that altering the degree of segmentation may require more relevant emotional or motivational signals. In our study, participants knew that they would receive the associated rewards, and their performance had only a limited influence on the final amount. This minimal contingency may have reduced the motivational significance of high-rewarded transitions, weakening their potential to increase segmentation effects. While the reward still carried positive valence, its motivational relevance may have been diminished. Previous studies have shown that emotional events can trigger segmentation and shape memory organization particularly when they are negatively salient, behaviorally consequential or personally motivational (Harris et al. 2025; McClay et al. 2023; Murty and Adcock 2017). Thus, it is possible that a stronger emotional or motivational context change might be necessary to generate segmentation regardless of the prediction error. Additionally, the extent of this effect may be shaped by both the emotional valence and the degree of arousal associated with the event.

Taken together, even though we observe segmentation in both conditions, our findings suggest that changes in reward value may be insufficient to alter the degree of segmentation. These findings help clarify the limits of motivational salience as a segmentation cue and encourage future research to examine how surprise, affective meaning, and learning interact to shape the dynamic structure of memory. Future studies could further explore whether segmentation can be modulated by emotional or motivational signals that vary in intensity or character, such as by manipulating the degree of emotional salience or comparing different types of emotional content. Such work may clarify how affective signals influence event boundaries and the temporal organization of episodic memory.

4. PART 3: RETROSPECTIVE EFFECTS OF EMOTION REGULATION ON EVENT SEGMENTATION

4.1 Introduction

Event segmentation refers to the cognitive process by which continuous streams of information are parsed into discrete, meaningful units or events in memory. This process helps structure and organize episodic memories, allowing us to make sense of ongoing experience and predict what might happen next (Zacks et al. 2007; Radvansky and Zacks 2017; Clewett et al. 2019). Previous studies investigated event segmentation as events take place, i.e., online, during the real-time perception and encoding of continuous experience. However, memories are not static records of experience; instead, they are dynamic and malleable representations that can be updated or reorganized after their initial formation, i.e., offline, outside the moment of perception (de Oliveira Alvares and Do-Monte 2021; Dunsmoor et al. 2022; Favila et al. 2020; Lee et al. 2017; Moscovitch et al. 2016; Scully et al. 2017; Tambini and Davachi 2019). Thus, although event segmentation has traditionally been studied as an online phenomenon, it is also crucial to understand how memory structure may shift retrospectively (offline) in response to later experience or reinterpretation.

Retrospective changes can occur in memory via the creation and deliberation of associations with other memories (Chang et al. 2021; Dudai et al. 2015; Landmann et al. 2014; Paller and Voss 2004), or memory itself acquires new meanings through undergoing different cognitive evaluations, such as new emotional attributions (Samide and Ritchey 2021). For example, when a category of studied items is later associated with reward or punishment, this association can retrospectively generalize to other items in the same category that were studied before the reward/punishment association was learned (Clewett et al. 2021; Dunsmoor et al. 2015; Oyarzún et al. 2016; Patil et al. 2017).

This dynamic structure of memory allows us to build predictive models of the world that can be updated with newly acquired information, enabling more accurate predictions of the future (Hohwy et al. 2021). For instance, imagine recalling a walk you took with your partner that initially seemed uneventful. Later, after learning that the conversation during that walk marked the beginning of a deeper conflict, you may retrospectively redefine the memory, segmenting it into two distinct parts: before and after the emotional shift. In this case, event segmentation occurs after the fact, shaped by new significance attributed to the experience. In contrast, some experiences may already be segmented at the time of encoding — for example, during an argument with your partner, you might immediately perceive a shift in tone or emotion and remember it as two segments: before and after the disagreement. Yet, even when segmentation is initially present, later cognitive reappraisal or reflection may reshape the internal boundaries or alter the perceived meaning of each segment. In both scenarios, the ability to revise and restructure memories based on motivationally relevant information enhances our capacity to adapt, forecast outcomes, and make more informed decisions in everyday life.

Although it has been demonstrated that newly learned information can influence memory retrospectively, it is unclear the effects of experiences on the segmentation of previously encoded memories. Accordingly, the main purpose of this section is to study the retrospective influences of emotional processes on event segmentation, or retro-segmentation, on previously encoded memories.

Emotional experiences are an essential factor in influencing memory, affecting both the strength and structure of what is remembered. Emotional arousal can prioritize the retention of goal-relevant information (Mather and Sutherland 2011), disrupt the sequential recall of events (Bisby and Burgess 2014), and bias memory for specific events (Talmi 2013). Such processing influences the organization of memories by amplifying the perceived salience of certain events or moments, thereby influencing how episodic memories are structured and segmented (McClay et al. 2023). Importantly, these influences are not limited to the moment of encoding; emotional processes can also reshape memory traces during consolidation and retrieval, by altering their accessibility, vividness, or meaning (Dunsmoor et al. 2015; Tambini and Davachi 2019). While prior studies have primarily examined how emotion affects single memory traces or specific associations at or near the time of encoding, less is known about whether and how the broader structure of memory, such as the segmentation of continuous experience, can be reshaped retrospectively based on later-acquired salient information or emotional processing. The current study addresses this gap by testing whether emotional processing can modulate event segmentation even after initial encoding.

Among the processes involved in emotional processing that are particularly relevant to memory modification, cognitive reappraisal stands out, as it involves active cognitive control and enables the re-evaluation of specific memories, facilitating the formation of new associations related to the original event (Gross 1998). Reappraisal involves cognitively reframing the emotional meaning of an event to change its impact (Gross 2002). It has been shown to influence emotional responses and how memories are encoded, stored, and later retrieved (Buhle et al. 2014; Samide and Ritchey 2020). Therefore, reactivating previous memories contributes to memory modification. By intentionally changing how one interprets a previously encoded emotional experience, reappraisal may reshape the internal boundaries of that memory, reorganizing it into different segments or altering its narrative structure. For example, an argument with a partner might later be seen not as a single moment, but as a series of phases—tension building, the conflict, and what followed—after rethinking about event. Such processing makes cognitive reappraisal an ideal tool for examining whether and how retro-segmentation can be triggered by top-down, evaluative processes. In this study, we therefore employed cognitive reappraisal alongside more passive and neutral control conditions to investigate its potential to modify the structure of previously encoded emotional events.

In addition to examining the general effects of emotional processing on retro-segmentation, the current study also considers how this process may vary across individuals. Prior research has shown that factors such as anxiety, depression, and post-traumatic stress symptoms can influence memory encoding, emotional processing, and cognitive control (Bisby et al. 2020; Rubin et al. 2008). By considering these individual differences, we aimed to explore whether variations in emotional or cognitive profiles predict the degree to which previously encoded events are segmented in memory.

To investigate the dynamics of retrospective segmentation in memory, we presented participants with negative stimuli among neutral everyday objects. After that, we asked them to engage with those previously encoded negative images in one of three ways: through cognitive reappraisal, by simply reflecting on the image, or by completing a filler task designed to divert attention away from emotional processing. Participants' temporal memory was assessed immediately after to examine the initial effects of retrospective evaluation on memory structure. We expected to see segmentation at temporal tasks regardless of the conditions due to high emotional arousal image at encoding. We expected to observe segmentation effects in temporal memory tasks across all conditions, given the presence of emotionally arousing stimuli during encoding. However, we hypothesized that segmentation would be strongest in the cognitive reappraisal condition, followed by the reflection condition, and weakest in the filler task condition, indicating the retrospective impact of varying levels of cognitive engagement with the previously encoded material. Additionally, we expected that emotion-driven segmentation to be positively correlated with higher PTSD, stait and trait anxiety, intrusive thoughts, negative affect, dysfunction in emotion regulation and depression scores.

4.2 Methods

4.2.1 Open Science Practices

The experiments and hypothesis reported in this article were not preregistered.

4.2.2 Ethical Approval

The study was conducted at University of California, Los Angeles (UCLA), United States. The experiment was approved by UCLA Institutional Review Boards (IRBs) and was in line with the principles of the Declaration of Helsinki (World Medical Organization 1964). Participants had provided written informed consent before the study, and they got course credit for their attendance.

4.2.3 Participants

A power analysis was conducted in G*Power 3.1 to estimate the appropriate sample size. This analysis was based on data from a highly matched event boundary paradigm, which used pairwise temporal order memory and temporal distance memory as indices of event segmentation (Harris et al. 2025). The average Cohen's d value (.56) is obtained from the effect size of temporal order and temporal distance judgments for boundary and non-boundary pairs. An alpha level of 0.05 and a power level of 0.80 showed that 40 participants would be necessary to obtain the weakest temporal memory effect.

We collected data from 48 participants (35 F, Mage = 19.9, SDage = 1.08). All participants were between the ages of 18-35, native or fluent English speakers, had normal or corrected-to-normal vision, and had no history of neurological trauma. 2 participants were removed due to being 2.5 standard deviations above or below the grand average of temporal order accuracy and temporal distance judgments regardless of the conditions. Analysis were conducted with 46 participants.

4.2.4 Materials

540 neutral daily life objects were selected from the existing datasets (Gabrieli et al. 1997; Kensinger et al. 2006). To induce emotional event boundaries, 15 negative valenced (M = 2.12, SD = 1.39) and highly arousing (M = 6.41, SD = 2.12) images were selected from the International Affective Picture System (IAPS) (Lang et al. 1997). We normalized the luminance of all object images and IAPS images using MATLAB's SHINE toolbox to limit any non-cognitive influences on pupil dilation responses. The experiment was designed using Psychopy Experiment Builder, version 2024.2.4 (Peirce et al. 2019).

4.2.4.1 Clinical questionnaires

At the end of the first session of the experiment, participants were asked to complete six questionnaires to assess their current mood states, emotion regulation abilities, depression level, trauma and anxiety symptomatology. Qualtrics was used to present these questionnaires including the 10-item emotion regulation questionnaire (ERQ: Gross and John 2003), the 20-item the Positive and Negative Affect Schedule (PANAS: Watson et al. 1988), the 16-item Dysregulation in Emotion Regulation Scale (DERS-16: Bjureberg et al. 2016), the 40-item State-Trait Anxiety Inventory Forms Y-1 and Y-2 (STAI: Spielberger 1983), the 5-item Persistent and Intrusive Negative Thoughts Scale (PINTS: Magson et al. 2019) the 20-item Posttraumatic Stress Disorder Checklist for DSM-5 (PCL-5: Blevins et al. 2015), and the 21-item Beck Depression Inventory (BDI: Beck et al. 1988). We also assessed the subjective evaluation of emotional regulation during the task on a Likert scale from 1 to 7 by asking, "How well did you use cognitive reappraisal to reduce your emotional response to the negative images?", "How much effort did you put into using reappraisal during the task?", and "How successful was that strategy in helping you regulate your emotions?".

4.2.4.2 Emotion regulation training

Before starting the main experiment, participants were trained on how to use cognitive reappraisal as a cognitive strategy in response to an emotionally negative image.

During the practice, participants were informed that they would see a negative image on the screen paired with either the letter "T" or "R". If the letter "R" appeared, they were instructed to apply a cognitive reappraisal strategy to the image; if the letter "T" appeared, they were asked to simply view the image and fully experience any feelings that naturally arose. They were also informed that this strategy would be used again in the second phase of the main experiment. To introduce reappraisal techniques, the experimenter presented an example negative image and described three reappraisal strategies adapted from McRae et al. (2008): (1) It is not real (e.g., the events depicted are staged or acted); (2) Things will improve (e.g., the situation will resolve over time); and (3) It is not as bad as it appears (e.g., the situation could be worse). Participants then practiced these instructions with four negative images, alternating between “R” and “T” trials, paced by the experimenter.

To ensure that participants correctly applied cognitive reappraisal during the R trials, they were asked to verbally share the reappraisal strategies they used for four negative images with the experimenter. The experimenter monitored these verbal reports to verify the correct use of reappraisal and address any misunderstandings or incorrect approaches. Following this, participants were presented with four additional negative images and asked to apply similar strategies internally, this time without speaking aloud. During this phase, the cue letter was displayed for 0.5 seconds, and images remained on the screen for 4 seconds, matching the timing used in the main experiment. Participants were informed that they would be required to use the cognitive reappraisal strategy during the second phase of the main experiment, and that they would have 8 seconds to implement it. The negative images used during the practice phase were not included in the main experiment.

4.2.5 Design

The experimental procedure is shown in Figure 4.1. The experiment took 90 minutes. There were 15 blocks, divided into three conditions (five for each): cognitive reappraisal, re-experience/think, and dot counting, used as a control. The order of the conditions was randomized for each participant by ensuring that they did not repeat twice in a row. There were three phases included: encoding, cognitive tasks, and a memory test. In the first phase, participants encoded 24 neutral images (a total of 360) and one emotional image (a total of 15). The image order was kept constant: 13 neutral, one emotional, 11 neutral. The image display duration was 4 seconds, and participants evaluated the images based on how much they liked the item, rating from 1 to 4 (1: not at all, 4: very much).

At the beginning and end of the second phase, participants completed a 45-second arrow task. They were instructed to indicate the direction of the arrows on the screen by pressing the keys (1 for left, 2 for right). This filler task was included to prevent potential emotional carryover effects from the encoding phase to the second phase, and from the second phase to the subsequent memory test. During the second phase, participants performed either one of the conditions after the arrow task. Task durations in this phase were equalized across conditions to eliminate confounding effects that could result from differences in time spent on each condition (see Figure 4.1.B).

For the reappraisal condition, the word cue “reappraisal” was shown on the screen for 8 seconds, and participants were asked to make an cognitive reappraisal about the just-encoded negative image. For the re-experience condition, the word “think” was displayed on the screen for 8 seconds, and participants were asked to simply think about the image. Following reappraisal and re-experience conditions, three questions were displayed on the screen for 4 seconds. The questions were implemented to evaluate the arousal, valence, and vividness regarding the negative image as follows: “How intense were your feelings when recalling the image?”, “How vivid or clear is the mental image that comes to mind when you think about this picture?”, and “How unpleasant did recalling that image make you feel?”.

For the dot-counting condition, dots in different numbers from 1 to 7 were displayed on the screen for a total of 20 seconds. Participants were asked to report the number of dots on the screen using a scale. This condition was included as a control to assess the direct impact of encountering an emotional boundary item during encoding on memory performance (e.g., Harris et al. 2025). The dot task allows us to assess temporal memory for the emotional boundary item without interacting with the emotional processing and cognitive reappraisal.

For the memory test, participants’ memory was assessed with temporal order and temporal distance judgment tasks. For temporal order memory, two neutral objects were displayed on the screen from the encoding list, and participants were asked to identify which object came first in chronological order. There were four choices: 1: ‘definitely left’; 2: ‘maybe left’; 3: ‘maybe right’; 4: ‘definitely right’. Temporal distance memory was assessed for the same object pair by asking how far apart in time the two items were in the list. There were four options to respond by using the same keys: ‘very close’, ‘close’, ‘far’, and ‘very far’, respectively. The distance between the image pairs was kept constant by three intervening objects. A total of nine object pairs were tested per list: three pre-boundary pairs, three emotional boundary-spanning pairs, and three post-boundary pairs. Therefore, there were 45 temporal order and distance judgments for each condition across 15 lists. The memory tests were self-paced, and the image pairs stayed on the screen for a maximum of 8 seconds.

4.3 Results

Analyses were conducted with JAMOVI 2.3 (2023). Repeated measures analysis of variance (ANOVA) was conducted to compare the within-subject differences for within vs. across boundary effects across conditions.

4.3.1 Temporal Order Memory

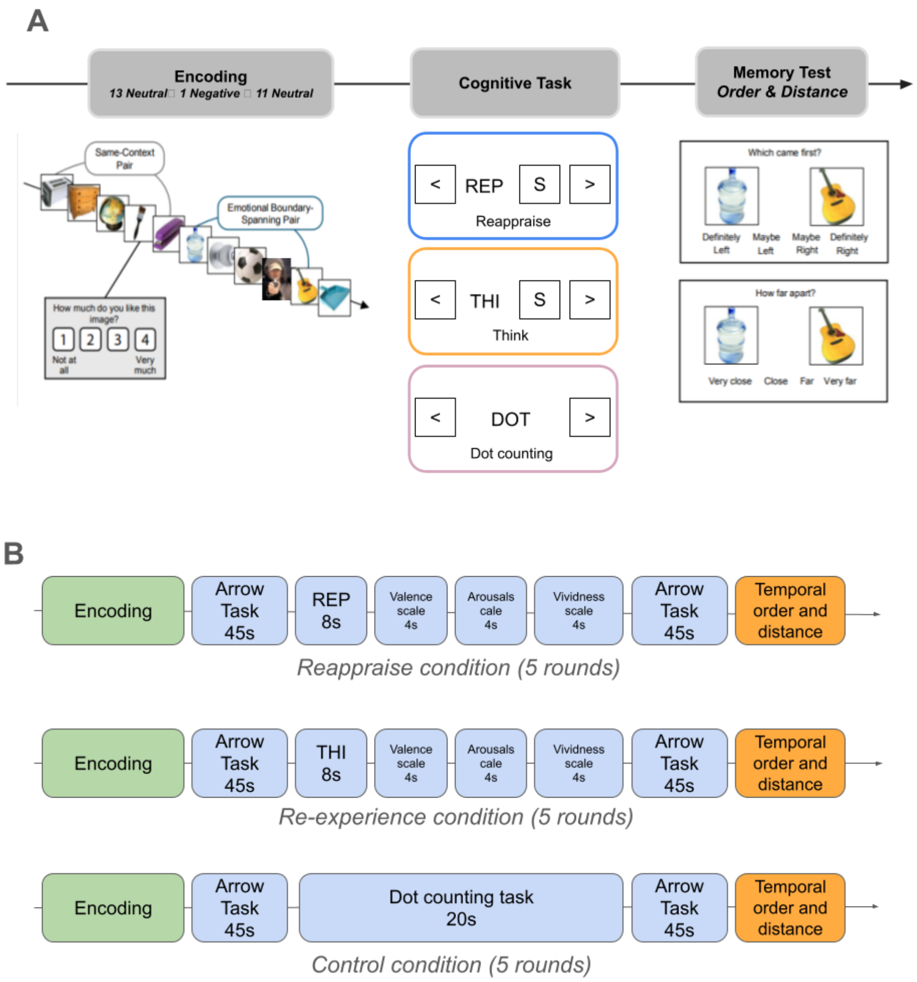
Temporal order memory accuracy was evaluated with 2 (Pair Type: emotional boundary-spanning, same-context pair) x 2 (Cognitive task: reappraise, think, and control) factorial design. Assumptions of repeated-measures ANOVA were met (ps > .05). Visual inspection of the Q-Q plot suggested that the residuals were approximately normally distributed. Additionally, Levene's tests indicated no significant violations of the homogeneity of variances assumption (ps > .05). There was a significant main effect of pair type on temporal order memory, $F(1, 45) = 4.98$, $p = .03$, n2p = 0.100 (Figure 3). Accordingly, same-context pairs indicated higher accuracy ($M = .64$, $SD = .08$) compared to boundary-spanning pairs ($M = .61$, $SD = .08$), $t(45) = 2.20$, $p = .01$. However, there was no significant main effect of condition, $F(2, 90) = 0.32$, $p = .72$, n2p = .007, nor a significant condition $\times$ pair type interaction, $F(2, 90) = 0.56$, $p = .57$, n2p = .012.

Follow-up comparisons with paired t-tests between pair types indicated that order memory was significantly higher for same-context pairs ($M = .63$, $SD = .10$) compared to boundary-spanning pairs ($M = .59$, $SD = .14$) in the think condition, $t(45) = 1.86$, $p = .03$. However, order memory did not significantly differ by pair type in reappraise, $t(45) = 1.32$, $p = .09$, and control condition, $t(45) = .30$, $p = .38$.

4.3.2 Temporal Distance Judgments

The same analysis design was used to assess the temporal distance judgments between pair types and conditions. Assumptions of repeated-measures ANOVA were met (ps > .05). Visual inspection of the Q-Q plot suggested that the residuals were

Figure 4.1 The design of the experiment including three phases; encoding, cognitive task and memory test (Section A). Participants learned 24 neutral and 1 negative arousal images. During second phase, they either do cognitive reappraisal about the negative image, think about the negative image, or dot counting task as a control condition. Reappraisal and think conditions were followed by three scales assessing the arousal, valence and vividness regarding the negative image. They performed another arrow task before moving to the third phase. In memory test, they performed temporal order and temporal distance tasks for image pairs from encoding. The section B indicates the detailed flow of each individual steps in the experiment.



approximately normally distributed. There was a significant main effect of pair type on temporal order memory, F(1, 45) = 12.30, p = .001, n2p = 0.21 (Figure 3). Accordingly, perceived temporal distance was higher for boundary-spanning pairs (M = 2.56, SD = .24) compared to same-context pairs (M = 2.47, SD = .20), t(45) = -3.41, p < .001. However, there was no significant main effect of condition, F(2, 90) = 1.90, p = .15, n2p = .041, nor a significant condition × pair type interaction, F(2, 90) = 2.95, p = .057, n2p = .062.

Follow-up comparisons with paired t-tests between pair types indicated that perceived temporal distance was significantly higher for boundary-spanning pairs (M = 2.60, SD = .28) compared to same-context pairs (M = 2.46, SD = .21) in the think condition, t(45) = -3.85, p < .001. Similarly, perceived temporal distance was higher for boundary-spanning pairs (M = 2.58, SD = .29) compared to same-context pairs (M = 2.47, SD = .25) in the reappraise condition, t(45) = -2.41, p = .01. However, there was no significant difference between pair types in the control condition, t(45) = -.45, p = .32.

Figure 4.2 Temporal order memory accuracy and temporal distance judgments across conditions and for each pair type

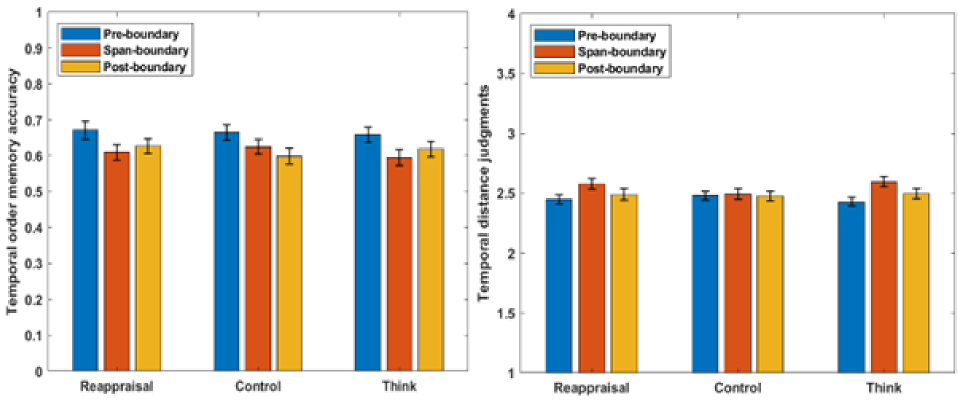
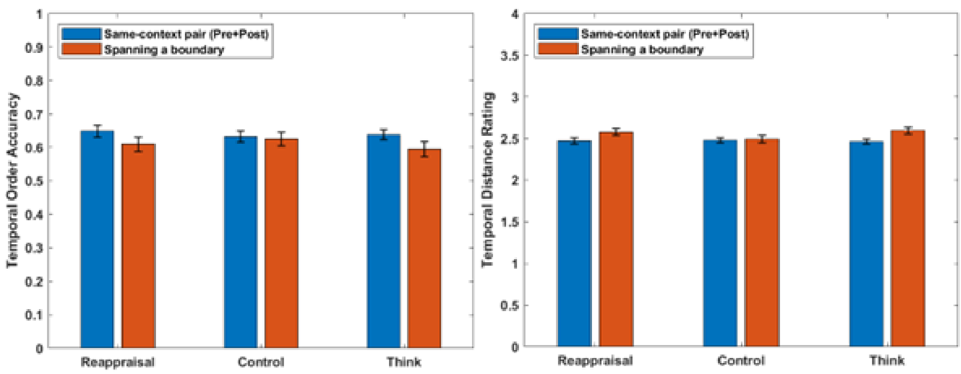


Figure 4.3 Temporal order memory accuracy and temporal distance judgments across conditions and for each pair type



4.3.3 The Relationship Between Individual Differences and Retro-segmentation

We examined the associations between temporal order memory, temporal distance judgments, and individual difference measures using Spearman's rho correlation. To this end, we first computed a segmentation score for each temporal measure. For temporal distance judgments, segmentation scores were calculated by subtracting same-context pair ratings from spanning-boundary pair ratings, such that higher scores indicated greater segmentation. For temporal order memory, segmentation scores were calculated by subtracting spanning-boundary accuracy from same-context accuracy, again reflecting greater segmentation with higher values. These calculations were performed separately for each condition.

Here, we reported the correlations between temporal measures and individual differences scores. There were positive correlations between the temporal order segmentation score in think condition with PANAS negativity score ($p = .35$, p = .016), and PINTS ($p = .31$, p = .031). Accordingly, people who felt more negative and have persistent intrusive negative thoughts, they indicated higher segmentation in think condition. There was no other significant correlation between temporal measures and segmentation scores (see Appendix Figure C.1).

4.4 Discussion

The present study investigated whether emotional processing, particularly cognitive reappraisal, can change the structure of previously encoded experiences, leading to retro-segmentation. Across conditions, we replicated classic segmentation effects: participants showed better temporal order memory and perceived greater temporal distance for same-context compared to boundary-spanning pairs. Moreover, we particularly indicated the segmentation of previously encoded experiences on think and reappraise conditions than control condition. These findings extend previous literature by showing that emotional processing of salient stimuli can influence not only the perception of events as they unfold but also the structure of memories that have already been encoded (Clewett et al. 2019; McClay et al. 2023; Harris et al. 2025).

Contrary to our hypothesis, cognitive reappraisal did not significantly enhance segmentation relative to the think or control conditions. While we expected that active reinterpretation of the emotional image would produce stronger segmentation by altering the internal representation of the event, we could not observe main condition effect on segmentation patterns. However, pairwise comparisons indicated that the segmentation patterns were only absent in the control condition. This indicates that retrospective emotional processing, whether through reappraisal or passive reflection, has a significant role in changing the structure of encoded memories.

Our findings are both consistent with and extend those of a previous study that examined similar emotional processing in the context of event segmentation (Harris et al. 2025). They also tested the effects of emotional processing on participants' ongoing experiences (i.e., online) using the same manipulation and similarly found condition-independent segmentation effects. By replicating their findings and incorporating a control condition, our study provides an evidence that it is not merely exposure to a negative stimulus, but emotional engagement with it, that drives changes in event segmentation.

In line with prior studies suggesting individual variability in emotional memory processing (Bisby et al. 2020; Rubin et al. 2008), we also explored whether cognitive or affective traits predicted susceptibility to retro-segmentation. Correlational analyses revealed that participants with higher negative affect and more persistent intrusive thoughts indicated higher segmentation in the think condition. This finding implies that individuals who are more emotionally reactive, prone to rumination may be more likely to impose boundaries on prior experiences when reflecting on them. This indicates a consistency with that negative emotional states heighten memory selectivity and disrupt continuity (Bisby and Burgess 2014), potentially leading to more segmentation.

The fact that this correlation emerged only in the think condition can also be interpreted as consistent with the influences of emotional processes on segmentation. Individuals who are more prone to negative affect and rumination may exaggerate the emotional reflecting in a given situation, which aligns with prior findings showing that higher PTSD is associated with increased segmentation and less segmentation agreement (Pitts et al. 2022; Sherrill et al. 2019). Importantly, this effect appears to extend to retrospectively processed experiences as well, suggesting that emotional tendencies can shape the structure of memory even after encoding has occurred.

To state the limitations of the current study, one issue can be mentioned. Even though participants were instructed to either do cognitive reappraisal or thinking, we cannot be sure about whether they are engaging them adequately. Also, they may do cognitive reappraisal in the think condition as well just because they were practicing both, which can be vice versa as well. To eliminate such limitation, physiological markers can be evaluated. For instance, participants' pupil dilation can be evaluated during second phase to see whether there is a difference in pupil dilation between conditions. In this case, increased pupil dilation will be associated with higher cognitive control that is expected to be seen during cognitive reappraisal compared to simple reflection and simple filler task.

Future research could evaluate four issues that enrich the findings of the current study. First, alternative forms of top-down modulation (e.g., narrative construction, or self-relevance manipulation) can be evaluated to understand the possible contributions of different processes to induce retro-segmentation. Second, retro-segmentation effects can be evaluated with the consolidation process, meaning that participants' memory performances can be evaluated 24 hours apart to consider whether the segmentation patterns will change with consolidation. Third, neuroimaging or pupillometry measures could help clarify whether reappraisal engages different cognitive or affective mechanisms than simple reflection. Fourth, individual difference factors such as emotion regulation style may moderate the extent to which emotional processing alters memory boundaries, which is a promising direction to understand more personalized models of memory structure.

Taken together, our findings provide a support for the idea that emotional processing, particularly reflection and reappraisal, can influence how previously encoded experiences are segmented in memory. Although cognitive reappraisal did not produce a significantly stronger effect than thinking, individual differences in negative affect and intrusive thoughts correlated with the degree of segmentation, highlighting the complex interplay between emotional traits and memory structure. This work contributes to emerging views that memory is not only shaped at the time of encoding, but continues to be reorganized and re-framed in light of new experiences.

5. GENERAL DISCUSSION

The present research offers a broadening understanding of event segmentation by evaluating its underlying factors, how different factors modulate the segmentation of ongoing experience, and whether the structure of encoded memories can be modulated by later processing. Also, we evaluated the emotional processing as a modulator for segmentation of experiences. Accordingly, we considered how perceived reward can change the structure of experiences, and whether down-regulation of emotions for encoded experiences can influence the structure of those memories. Additionally, we evaluated how individual differences with emotional processing modulate the segmentation patterns. These studies contribute both to understand the processing of segmentation and dynamic nature of episodic memory.

Part 1 introduces a strong alternative view to the long lasting understanding of event segmentation which was considered the prediction errors were the main leading mechanisms to generate discrete events. Across four experiments, the results consistently showed that segmentation was stronger when contextual stability, such as consistent task rules or object categories, were maintained. Critically, when prediction errors were manipulated while having contextual continuity (e.g., unpredictable transitions), segmentation did not reliably increase. These results challenge core assumptions of event segmentation theory and instead highlight contextual stability as the dominant factor in segmenting experience.

Part 2 evaluated whether online changes in reward associations could modulate event segmentation. Although participants reliably showed better temporal order memory and shorter perceived temporal distances for within-event compared to across-event pairs, no consistent segmentation differences observed between high-rewarded and low-rewarded conditions. Even when the perceptual salience of transitions was reduced to enhance the influence of motivational cues, reward value alone did not significantly shape event boundaries. This suggests that reward salience may not be a strong modulator of segmentation strength. Alternatively, segmentation may reflect a relatively inflexible structure, such that its degree cannot be easily altered by motivational factors.

Part 3 tested whether emotional processing, particularly cognitive reappraisal, could retrospectively structure the segmentation of already encoded experiences. Across all conditions, including reappraisal, thinking, and a control task, classic segmentation effects were observed. However, no significant differences emerged across conditions. Interestingly, pairwise comparisons indicated that segmentation appeared strongest in the reappraisal and thinking conditions compared to control, and individual differences such as negative affect and intrusive thoughts predicted stronger segmentation in the think condition. These findings suggest that emotional processing can change the structure of past events, and that individual affective profiles may play a critical role in this process.

Across studies, we also confirmed our findings regarding the underlying factors of event segmentation. In Part 1, we found that contextual stability is a dominant factor in generating segmented events, rather than mere prediction errors (i.e., unexpected transitions within a given context). Accordingly, encountering a single deviant stimulus was not sufficient to elicit segmentation. In line with this, in Part 3, we did not observe differences in temporal memory between same-context and boundary-spanning pairs in the control condition, whereas such differences were present in the reappraisal and think conditions. This suggests that even if the stimulus is emotionally salient, encountering it as a single deviant category may not be sufficient to segment an experience into meaningful units. Instead, segmentation appears to emerge when individuals engage in emotional processing of that experience, which may generate a sense of contextual structure. Actively trying to understand a past experience, or attempting to down-regulate the negative emotions associated with it, may require evaluating that experience within a broader interpretive framework, essentially reconstructing a context around the memory.

Another point to consider across studies in understanding the nature of event segmentation is that the dividing memories into discrete units may not operate through a highly sensitive or fine-tuned mechanism. In Part 2, our findings suggested that even when certain moments within an experience become relatively more salient or prioritized, this shift does not meaningfully change the segmentation process. Similarly, in Part 3, we did not observe a significant difference in segmentation between the reappraisal and think conditions. Although reappraisal involves greater cognitive effort, the act of emotional processing itself, rather than its specific form or intensity, appeared to be the critical factor influencing segmentation. In other words, while emotional engagement contributed to structural changes in memory, variations in the depth or strategy of emotional processing did not result in significantly different segmentation patterns. These findings suggest that, although memory segmentation may require a stable contextual framework, it does not appear to be finely tuned to subtle differences in emotional processing. From an evolutionary perspective, this could reflect an adaptive feature of memory: rather than creating distinct memory units for varying degrees of emotional engagement, the system may favor efficiency by segmenting experiences only when major contextual shifts occur, thereby conserving cognitive resources.

That said, this interpretation should be approached with caution. In the present studies, retrospective evaluation of experiences occurred under relatively mild manipulations, such as cognitive reappraisal and modest differences in reward value. It remains possible that under different task demands, reward contingencies, or emotional processing frameworks, segmentation could vary more substantially across conditions. For instance, emotional conditioning (Dunsmoor et al. 2015), affective storytelling or narrative reframing (Habermas and Bluck 2000), or emotional imagery involving autobiographical recall (Holland and Kensinger 2010) may more strongly influence the degree of segmentation. Future research should take these possibilities into account, as doing so may shed light on how we reshape our experiences in everyday life and clarify which specific factors make the structure of episodic memory more or less susceptible to change.

Findings of the present research offers important implications to existing theories of memory organization by demonstrating that segmentation is shaped by a dynamic interplay of contextual, motivational, and emotional factors. First, the results highlight contextual stability, rather than prediction error, as the primary driver of event boundaries, suggesting that continuity and internal coherence may be more effective cues for structuring memory than mere surprise or mismatch. Second, while reward value is known to enhance memory for individual items, it does not appear to modulate the degree of event segmentation, pointing to a possibility of an inflexible structure compared to single representations. Third, the findings show that segmentation can be retrospectively modified through emotional processing. However, the absence of a clear difference between cognitive reappraisal and thinking conditions suggests that it is the act of emotional engagement itself, rather than the specific strategy used, that plays a key role in restructuring memory. This effect may be particularly pronounced in individuals with higher emotional reactivity. Finally, the finding that individuals with higher negative affect or more intrusive thoughts tend to show stronger segmentation highlights the influence of emotional traits on memory organization. This suggests that how we segment our experiences in memory may, in part, reflect stable aspects of our emotional makeup.

BIBLIOGRAPHY

Bailey, Heather R., Christopher A. Kurby, Tania Giovannetti, and Jeffrey M. Zacks. 2013. "Action Perception Predicts Action Performance." *Neuropsychologia* 51(11): 2294–2304.

Baldassano, Christopher, Janice Chen, Asieh Zadbood, Jonathan W. Pillow, Uri Hasson, and Kenneth A. Norman. 2017. "Discovering Event Structure in Continuous Narrative Perception and Memory." *Neuron* 95(3): 709–721.e5.

Baldassano, Christopher, Uri Hasson, and Kenneth A. Norman. 2018. "Representation of Real-World Event Schemas during Narrative Perception." *The Journal of Neuroscience* 38(45): 9689–9699.

Bein, Oded, Natalie A. Plotkin, and Lila Davachi. 2021. "Mnemonic Prediction Errors Promote Detailed Memories." *Learning & Memory* 28(11): 422–434.

Ben-Yakov, Aya, Neetai Eshel, and Yadin Dudai. 2013. "Hippocampal Immediate Poststimulus Activity in the Encoding of Consecutive Naturalistic Episodes." *Journal of Experimental Psychology: General* 142(4): 1255–1263.

Bilkey, David K., and Charlotte Jensen. 2021. "Neural Markers of Event Boundaries." *Topics in Cognitive Science* 13(1): 128–141.

Bisby, James A., and Neil Burgess. 2014. "Negative Affect Impairs Associative Memory but Not Item Memory." *Learning & Memory* 21(1): 21–27.

Bjureberg, Johan, Brjánn Ljótsson, Matthew T. Tull, Erik Hedman, Hanna Sahlin, Lars-Gunnar Lundh, Jonas Bjärehed, David DiLillo, Terri Messman-Moore, Clara Hellner Gumpert, and Kim L. Gratz. 2016. "Development and Validation of a Brief Version of the Difficulties in Emotion Regulation Scale: The DERS-16." *Journal of Psychopathology and Behavioral Assessment* 38(2): 284–296.

Blevins, Christy A., Frank W. Weathers, Margaret T. Davis, Tracy K. Witte, and Jessica L. Domino. 2015. "The Posttraumatic Stress Disorder Checklist for *DSM-5* (PCL-5): Development and Initial Psychometric Evaluation." *Journal of Traumatic Stress* 28(6): 489–498.

Braun, Erin Kendall, G. Elliott Wimmer, and Daphna Shohamy. 2018. "Retroactive and Graded Prioritization of Memory by Reward." *Nature Communications* 9(1): 4886.

Buhle, J. T., J. A. Silvers, T. D. Wager, R. Lopez, C. Onyemekwu, H. Kober, J. Weber, and K. N. Ochsner. 2014. "Cognitive Reappraisal of Emotion: A Meta-Analysis of Human Neuroimaging Studies." *Cerebral Cortex* 24(11): 2981–2990.

Butz, Martin V., Asya Achimova, David Bilkey, and Alistair Knott. 2021. "Event-Predictive Cognition: A Root for Conceptual Human Thought." *Topics in Cognitive Science* 13(1): 10–24.

Chang, Claire H. C., Christina Lazaridi, Yaara Yeshurun, Kenneth A. Norman, and Uri Hasson. 2021. "Relating the Past with the Present: Information Integration and Segregation during Ongoing Narrative Processing." *Journal of Cognitive Neuroscience* 33(6): 1106–1128.

Chen, Janice, Yuan Chang Leong, Christopher J Honey, Chung H Yong, Kenneth A Norman, and Uri Hasson. 2017. "Shared Memories Reveal Shared Structure in Neural Activity Across Individuals." *Nature Neuroscience* 20(1): 115–125.

Clewett, David, and Lila Davachi. 2017. "The Ebb and Flow of Experience Determines the Temporal Structure of Memory." *Current Opinion in Behavioral Sciences* 17: 186–193.

Clewett, David, and Mason McClay. 2024. "Emotional Arousal Lingers in Time to Bind Discrete Episodes in Memory." *Cognition and Emotion* 39(1): 97–116.

Clewett, David, Camille Gasser, and Lila Davachi. 2020. "Pupil-Linked Arousal Signals Track the Temporal Organization of Events in Memory." *Nature Communications* 11(1): 4007.

Clewett, David, Joseph Dunsmoor, Shelby L. Bachman, Elizabeth A. Phelps, and Lila Davachi. 2022. "Survival of the Salient: Aversive Learning Rescues Otherwise Forgettable Memories via Neural Reactivation and Post-Encoding Hippocampal Connectivity." *Neurobiology of Learning and Memory* 187: 107572.

Clewett, David, Sarah DuBrow, and Lila Davachi. 2019. "Transcending Time in the Brain: How Event Memories Are Constructed from Experience." *Hippocampus* (3): 162–183.

Conway, Martin A. 2009. "Episodic Memories." *Neuropsychologia* 47(11): 2305–2313.

Davachi, Lila, and Sarah DuBrow. 2015. "How the Hippocampus Preserves Order: The Role of Prediction and Context." *Trends in Cognitive Sciences* 19(2): 92–99.

De Oliveira Alvares, Lucas, and Fabricio H. Do-Monte. 2021. "Understanding the Dynamic and Destiny of Memories." *Neuroscience & Biobehavioral Reviews* 125: 592–607.

Demblon, Julie, and Arnaud D'Argembeau. 2014. "The Organization of Prospective Thinking: Evidence of Event Clusters in Freely Generated Future Thoughts." *Consciousness and Cognition* 24: 75–83.

DuBrow, Sarah, and Lila Davachi. 2013. "The Influence of Context Boundaries on Memory for the Sequential Order of Events." *Journal of Experimental Psychology: General* 142(4): 1277–1286.

DuBrow, Sarah, and Lila Davachi. 2014. "Temporal Memory Is Shaped by Encoding Stability and Intervening Item Reactivation." *The Journal of Neuroscience* 34(42): 13998–14005.

DuBrow, Sarah, and Lila Davachi. 2016. "Temporal Binding Within and Across Events." *Neurobiology of Learning and Memory* 134: 107–114.

Dudai, Yadin, Avi Karni, and Jan Born. 2015. “The Consolidation and Transformation of Memory.” *Neuron* 88(1): 20–32.

Dunsmoor, Joseph E., Vishnu P. Murty, David Clewett, Elizabeth A. Phelps, and Lila Davachi. 2022. “Tag and Capture: How Salient Experiences Target and Rescue Nearby Events in Memory.” *Trends in Cognitive Sciences* 26(9): 782–795.

Dunsmoor, Joseph E., Vishnu P. Murty, Lila Davachi, and Elizabeth A. Phelps. 2015. “Emotional Learning Selectively and Retroactively Strengthens Memories for Related Events.” *Nature* 520(7547): 345–348.

Eisenberg, Michelle L., Jeffrey M. Zacks, and Shaney Flores. 2018. “Dynamic Prediction During Perception of Everyday Events.” *Cognitive Research: Principles and Implications* 3(1): 53.

Ezzyat, Youssef, and Lila Davachi. 2011. “What Constitutes an Episode in Episodic Memory?.” *Psychological Science* 22(2): 243–252.

Ezzyat, Youssef, and Lila Davachi. 2014. “Similarity Breeds Proximity: Pattern Similarity within and across Contexts Is Related to Later Mnemonic Judgments of Temporal Proximity.” *Neuron* 81(5): 1179–1189.

Farrell, Simon. 2012. “Temporal Clustering and Sequencing in Short-Term Memory and Episodic Memory.” *Psychological Review* 119(2): 223–271.

Favila, Serra E., Hongmi Lee, and Brice A. Kuhl. 2020. “Transforming the Concept of Memory Reactivation.” *Trends in Neurosciences* 43(12): 939–950.

Franklin, Nicholas T, Kenneth A Norman, Charan Ranganath, Jeffrey M Zacks, and Samuel J Gershman. 2020. “Structured Event Memory: A Neuro-Symbolic Model of Event Cognition.”.

Gold, David A., Jeffrey M. Zacks, and Shaney Flores. 2017. “Effects of Cues to Event Segmentation on Subsequent Memory.” *Cognitive Research: Principles and Implications* 2(1): 1.

Gong, Mengyuan, and Sheng Li. 2014. “Learned Reward Association Improves Visual Working Memory.” *Journal of Experimental Psychology: Human Perception and Performance* 40(2): 841–856.

Greve, Andrea, Elisa Cooper, Roni Tibon, and Richard N. Henson. 2019. “Knowledge Is Power: Prior Knowledge Aids Memory for Both Congruent and Incongruent Events, but in Different Ways.” *Journal of Experimental Psychology: General* 148(2): 325–341.

Grisoni, Luigi, Rosario Tomasello, and Friedemann Pulvermüller. 2021. “Correlated Brain Indexes of Semantic Prediction and Prediction Error: Brain Localization and Category Specificity.” *Cerebral Cortex* 31(3): 1553–1568.

Gross, James J. 1998. “Antecedent- and Response-Focused Emotion Regulation: Divergent Consequences for Experience, Expression, and Physiology.” *Journal of Personality and Social Psychology* 74(1): 224–237.

Gross, James J. 2002. “Emotion Regulation: Affective, Cognitive, and Social Consequences.” *Psychophysiology* 39(3): 281–291.

Gross, James J., and Oliver P. John. 2003. “Individual Differences in Two Emotion Regulation Processes: Implications for Affect, Relationships, and Well-Being.” *Journal of Personality and Social Psychology* 85(2): 348–362.

Güler, Berna, Fatih Serin, and Eren Gunseli. 2023. Prediction Error Is Out of Context: The Dominance of Contextual Stability in Segmenting Episodic Events. preprint PsyArXiv.

Güler, Berna, Zeynep Adıgüzel, Bilge Uysal, and Eren Günseli. 2024. “Discrete Memories of a Continuous World: A Working Memory Perspective on Event Segmentation.” *Current Research in Behavioral Sciences* 6: 100145.

Habermas, Tilmann, and Susan Bluck. 2000. “Getting a Life: The Emergence of the Life Story in Adolescence.” *Psychological Bulletin* 126(5): 748–769.

Hahamy, Avital, Haim Dubossarsky, and Timothy E. J. Behrens. 2023. “The Human Brain Reactivates Context-Specific Past Information at Event Boundaries of Naturalistic Experiences.” *Nature Neuroscience* 26(6): 1080–1089.

Hard, Bridgette Martin, Meredith Meyer, and Dare Baldwin. 2019. “Attention Reorganizes as Structure Is Detected in Dynamic Action.” *Memory & Cognition* 47(1): 17–32.

Harris, Bailey, Mason McClay, and David Clewett. 2025. “Cognitive Reappraisal Influences the Organization of Emotional Episodes in Memory.”.

Heusser, Andrew C., Youssef Ezzyat, Ilana Shiff, and Lila Davachi. 2018. “Perceptual Boundaries Cause Mnemonic Trade-Offs Between Local Boundary Processing and Across-Trial Associative Binding.” *Journal of Experimental Psychology: Learning, Memory, and Cognition* 44(7): 1075–1090.

Hohwy, Jakob, Augustus Hebblewhite, and Tom Drummond. 2021. “Events, Event Prediction, and Predictive Processing.” *Topics in Cognitive Science* 13(1): 252–255.

Holland, Alisha C., and Elizabeth A. Kensinger. 2010. “Emotion and Autobiographical Memory.” *Physics of Life Reviews* 7(1): 88–131.

Horner, Aidan J., James A. Bisby, Aijing Wang, Katrina Bogus, and Neil Burgess. 2016. “The Role of Spatial Boundaries in Shaping Long-Term Event Representations.” *Cognition* 154: 151–164.

Huff, Markus, Frank Papenmeier, and Jeffrey M. Zacks. 2012. “Visual Target Detection Is Impaired at Event Boundaries.” *Visual Cognition* 20(7): 848–864.

Infanti, Elisa, Clayton Hickey, and Massimo Turatto. 2015. “Reward Associations Impact Both Iconic and Visual Working Memory.” *Vision Research* 107: 22–29.

Kalbe, Felix, and Lars Schwabe. 2021. “On the Search for a Selective and Retroactive Strengthening of Memory: Is There Evidence for Category-Specific Behavioral Tagging?.” *Journal of Experimental Psychology: General* .

Kim, Ghootae, Jarrod A. Lewis-Peacock, Kenneth A. Norman, and Nicholas B. Turk-Browne. 2014. "Pruning of Memories by Context-Based Prediction Error." *Proceedings of the National Academy of Sciences* 111(24): 8997–9002.

Kurby, Christopher A., and Jeffrey M. Zacks. 2008. "Segmentation in the Perception and Memory of Events." *Trends in Cognitive Sciences* 12(2): 72–79.

Landmann, Nina, Marion Kuhn, Hannah Piosczyk, Bernd Feige, Chiara Baglioni, Kai Spiegelhalder, Lukas Frase, Dieter Riemann, Annette Sterr, and Christoph Nissen. 2014. "The Reorganisation of Memory During Sleep." *Sleep Medicine Reviews* 18(6): 531–541.

Lee, Jonathan L.C., Karim Nader, and Daniela Schiller. 2017. "An Update on Memory Reconsolidation Updating." *Trends in Cognitive Sciences* 21(7): 531–545.

Liu, Wei, Yingjie Shi, James N Cousins, Nils Kohn, and Guillén Fernández. 2022. "Hippocampal-Medial Prefrontal Event Segmentation and Integration Contribute to Episodic Memory Formation." *Cerebral Cortex* 32(5): 949–969.

Loh, Eleanor, Matthew Deacon, Lieke de Boer, Raymond J. Dolan, and Emrah Duzel. 2016. "Sharing a Context with Other Rewarding Events Increases the Probability That Neutral Events Will Be Recollected." *Frontiers in Human Neuroscience* 9.

Loock, Kaja, Felix Kalbe, and Lars Schwabe. 2025. "Cognitive Mechanisms of Aversive Prediction Error-Induced Memory Enhancements." *Journal of Experimental Psychology: General* 154(4): 1102–1121.

Magson, Natasha R., Ronald M. Rapee, Jasmine Fardouly, Miriam K. Forbes, Cele E. Richardson, Carly J. Johnco, and Ella L. Oar. 2019. "Measuring Repetitive Negative Thinking: Development and Validation of the Persistent and Intrusive Negative Thoughts Scale (PINTS)." *Psychological Assessment* 31(11): 1329–1339.

Mather, Mara, and Matthew R. Sutherland. 2011. "Arousal-Biased Competition in Perception and Memory." *Perspectives on Psychological Science* 6(2): 114–133.

McClay, Mason, Matthew E. Sachs, and David Clewett. 2023. "Dynamic Emotional States Shape the Episodic Structure of Memory." *Nature Communications* 14(1): 6533.

McRae, Kateri, Kevin N. Ochsner, Iris B. Mauss, John J. D. Gabrieli, and James J. Gross. 2008. "Gender Differences in Emotion Regulation: An fMRI Study of Cognitive Reappraisal." *Group Processes & Intergroup Relations* 11(2): 143–162.

Michelmann, Sebastian, Amy R. Price, Bobbi Aubrey, Camilla K. Strauss, Werner K. Doyle, Daniel Friedman, Patricia C. Dugan, Orrin Devinsky, Sasha Devore, Adeen Flinker, Uri Hasson, and Kenneth A. Norman. 2021. "Moment-by-Moment Tracking of Naturalistic Learning and Its Underlying Hippocampo-Cortical Interactions." *Nature Communications* 12(1): 5394.

Michelmann, Sebastian, Uri Hasson, and Kenneth A. Norman. 2023. "Evidence That Event Boundaries Are Access Points for Memory Retrieval." *Psychological Science* 34(3): 326–344.

Miendlarzewska, Ewa A., Daphne Bavelier, and Sophie Schwartz. 2016. "Influence of Reward Motivation on Human Declarative Memory." *Neuroscience & Biobehavioral Reviews* 61: 156–176.

Moscovitch, Morris, Roberto Cabeza, Gordon Winocur, and Lynn Nadel. 2016. "Episodic Memory and Beyond: The Hippocampus and Neocortex in Transformation." *Annual Review of Psychology* 67(1): 105–134.

Murty, Vishnu P., and R. Alison Adcock. 2017. "Distinct Medial Temporal Lobe Network States as Neural Contexts for Motivated Memory Formation." In *The Hippocampus from Cells to Systems*, ed. Deborah E. Hannula, and Melissa C. Duff. Cham: Springer International Publishing pp. 467–501.

Nolden, Sophie, Gözem Turan, Berna Güler, and Eren Günseli. 2024. "Prediction Error and Event Segmentation in Episodic Memory." *Neuroscience & Biobehavioral Reviews* p. 105533.

Ortiz-Tudela, Javier, Sophie Nolden, Francesco Pupillo, Isabelle Ehrlich, Iryna Schommartz, Gözem Turan, and Yee Lee Shing. 2023. "Not What u Expect: Effects of Prediction Errors on Item Memory." *Journal of Experimental Psychology: General* 152(8): 2160–2176.

Oyarzún, Javiera P., Pau A. Packard, Ruth de Diego-Balaguer, and Lluis Fuentemilla. 2016. "Motivated Encoding Selectively Promotes Memory for Future Inconsequential Semantically-Related Events." *Neurobiology of Learning and Memory* 133: 1–6.

Ozdemir, Şahcan, Yağmur Damla Şentürk, Nursima Ünver, Can Demircan, Christian N. L. Olivers, Tobias Egner, and Eren Günseli. 2024. "Effects of Context Changes on Memory Reactivation." *The Journal of Neuroscience* 44(36): e2096232024.

Paller, Ken A., and Joel L. Voss. 2004. "Memory Reactivation and Consolidation During Sleep." *Learning & Memory* 11(6): 664–670.

Palombo, Daniela J., and Chantelle Cocquyt. 2020. "Emotion in Context: Remembering When." *Trends in Cognitive Sciences* 24(9): 687–690.

Patil, Anuya, Vishnu P. Murty, Joseph E. Dunsmoor, Elizabeth A. Phelps, and Lila Davachi. 2017. "Reward Retroactively Enhances Memory Consolidation for Related Items." *Learning & Memory* 24(1): 65–69.

Pettijohn, Kyle A., and Gabriel A. Radvansky. 2016. "Narrative Event Boundaries, Reading Times, and Expectation." *Memory & Cognition* 44(7): 1064–1075.

Pitts, Barbara L., Michelle L. Eisenberg, Heather R. Bailey, and Jeffrey M. Zacks. 2022. "PTSD Is Associated with Impaired Event Processing and Memory for Everyday Events." *Cognitive Research: Principles and Implications* 7(1): 35.

Polyn, Sean M., Kenneth A. Norman, and Michael J. Kahana. 2009. “A Context Maintenance and Retrieval Model of Organizational Processes in Free Recall.” *Psychological Review* 116(1): 129–156.

Pradhan, Rujuta, and Devpriya Kumar. 2022. “Event Segmentation and Event Boundary Advantage: Role of Attention and Postencoding Processing.” *Journal of Experimental Psychology: General* 151(7): 1542–1555.

Pu, Yi, Xiang-Zhen Kong, Charan Ranganath, and Lucia Melloni. 2022. “Event Boundaries Shape Temporal Organization of Memory by Resetting Temporal Context.” *Nature Communications* 13(1): 622.

Pupillo, Francesco, Javier Ortiz-Tudela, Rasmus Bruckner, and Yee Lee Shing. 2023. “The Effect of Prediction Error on Episodic Memory Encoding Is Modulated by the Outcome of the Predictions.” *npj Science of Learning* 8(1): 18.

Qiu, Ruyi, Malte Möller, Iring Koch, Christian Frings, and Susanne Mayr. 2023. “The Influence of Event Segmentation by Context on Stimulus–Response Binding.” *Journal of Experimental Psychology: Human Perception and Performance* 49(3): 355–369.

Radvansky, Gabriel A. 2012. “Across the Event Horizon.” *Current Directions in Psychological Science* 21(4): 269–272.

Radvansky, Gabriel A., Kyle A. Pettijohn, and Joonsung Kim. 2015. “Walking Through Doorways Causes Forgetting: Younger and Older Adults.” *Psychology and Aging* 30(2): 259–265.

Raymond, Jane E., and Jennifer L. O’Brien. 2009. “Selective Visual Attention and Motivation: The Consequences of Value Learning in an Attentional Blink Task.” *Psychological Science* 20(8): 981–988.

Reagh, Zachariah M., Angelique I. Delarazan, Alexander Garber, and Charan Ranganath. 2020. “Aging Alters Neural Activity at Event Boundaries in the Hippocampus and Posterior Medial Network.” *Nature Communications* 11(1): 3980.

Reynolds, Jeremy R., Jeffrey M. Zacks, and Todd S. Braver. 2007. “A Computational Model of Event Segmentation from Perceptual Prediction.” *Cognitive Science* 31(4): 613–643.

Rouhani, Nina, Kenneth A. Norman, and Yael Niv. 2018. “Dissociable Effects of Surprising Rewards on Learning and Memory.” *Journal of Experimental Psychology: Learning, Memory, and Cognition* 44(9): 1430–1443.

Rouhani, Nina, Kenneth A. Norman, Yael Niv, and Aaron M. Bornstein. 2020. “Reward Prediction Errors Create Event Boundaries in Memory.” *Cognition* 203: 104269.

Rouhani, Nina, Yael Niv, Michael J. Frank, and Lars Schwabe. 2023. “Multiple Routes to Enhanced Memory for Emotionally Relevant Events.” *Trends in Cognitive Sciences* 27(9): 867–882.

Samide, Rosalie, and Maureen Ritchey. 2021. "Reframing the Past: Role of Memory Processes in Emotion Regulation." *Cognitive Therapy and Research* 45(5): 848–857.

Sandry, Joshua, Mark D. Zuppichini, and Timothy J. Ricker. 2020. "Attentional Flexibility and Prioritization Improves Long-Term Memory." *Acta Psychologica* 208: 103104.

Schapiro, Anna C, Timothy T Rogers, Natalia I Cordova, Nicholas B Turk-Browne, and Matthew M Botvinick. 2013. "Neural Representations of Events Arise from Temporal Community Structure." *Nature Neuroscience* 16(4): 486–492.

Schubotz, Ricarda I., Franziska M. Korb, Anne-Marike Schiffer, Waltraud Stadler, and D. Yves von Cramon. 2012. "The Fraction of an Action Is More Than a Movement: Neural Signatures of Event Segmentation in fMRI." *NeuroImage* 61(4): 1195–1205.

Scully, Iiona D., Lucy E. Napper, and Almut Hupbach. 2017. "Does Reactivation Trigger Episodic Memory Change? A Meta-Analysis." *Neurobiology of Learning and Memory* 142: 99–107.

Sherman, Brynn E., Sarah DuBrow, Jonathan Winawer, and Lila Davachi. 2023. "Mnemonic Content and Hippocampal Patterns Shape Judgments of Time." *Psychological Science* 34(2): 221–237.

Sherrill, Andrew M., Christopher A. Kurby, Michelle M. Lilly, and Joseph P. Magliano. 2019. "The Effects of State Anxiety on Analogue Peritraumatic Encoding and Event Memory: Introducing the Stressful Event Segmentation Paradigm." *Memory* 27(2): 124–136.

Shim, Sunjae, Franck B. Mugisho, Lila Davachi, and Christopher Baldassano. 2024. "Generating Event Boundaries in Memory Without Prediction Error.".

Shin, N. Y., T. Y. Lee, E. Kim, and J. S. Kwon. 2014. "Cognitive Functioning in Obsessive-Compulsive Disorder: A Meta-Analysis." *Psychological Medicine* 44(6): 1121–1130.

Siefke, Brian M., Troy A. Smith, and Per B. Sederberg. 2019. "A Context-Change Account of Temporal Distinctiveness." *Memory & Cognition* 47(6): 1158–1172.

Sinclair, Alyssa H., Grace M. Manalili, Iva K. Brunec, R. Alison Adcock, and Morgan D. Barense. 2021. "Prediction Errors Disrupt Hippocampal Representations and Update Episodic Memories." *Proceedings of the National Academy of Sciences* 118(51): e2117625118.

Sols, Ignasi, Sarah DuBrow, Lila Davachi, and Lluís Fuentemilla. 2017. "Event Boundaries Trigger Rapid Memory Reinstatement of the Prior Events to Promote Their Representation in Long-Term Memory." *Current Biology* 27(22): 3499–3504.e4.

Speer, Nicole K., Jeffrey M. Zacks, and Jeremy R. Reynolds. 2007. "Human Brain Activity Time-Locked to Narrative Event Boundaries." *Psychological Science* 18(5): 449–455.

Speer, Nicole K., Khena M. Swallow, and Jeffery M. Zacks. 2003. "Activation of Human Motion Processing Areas During Event Perception." *Cognitive, Affective, & Behavioral Neuroscience* 3(4): 335–345.

Spielberger, Charles D. 2012. "State-Trait Anxiety Inventory for Adults." https://doi.apa.org/doi/10.1037/t06496-000.

Swallow, Khena M., Adam W. Broitman, Elizabeth Riley, and Hamid B. Turker. 2022. "Grounding the Attentional Boost Effect in Events and the Efficient Brain." *Frontiers in Psychology* 13: 892416.

Swallow, Khena M., Jeffrey M. Zacks, and Richard A. Abrams. 2009. "Event Boundaries in Perception Affect Memory Encoding and Updating." *Journal of Experimental Psychology: General* 138(2): 236–257.

Talmi, Deborah. 2013. "Enhanced Emotional Memory: Cognitive and Neural Mechanisms." *Current Directions in Psychological Science* 22(6): 430–436.

Talmi, Deborah, Lynn J. Lohnas, and Nathaniel D. Daw. 2019. "A Retrieved Context Model of the Emotional Modulation of Memory." *Psychological Review* 126(4): 455–485.

Tambini, Arielle, and Lila Davachi. 2019. "Awake Reactivation of Prior Experiences Consolidates Memories and Biases Cognition." *Trends in Cognitive Sciences* 23(10): 876–890.

Tulving, Endel. 1993. "What Is Episodic Memory?" *Current Directions in Psychological Science* 2(3): 67–70.

Tulving, Endel. 2002. "Episodic Memory: From Mind to Brain." *Annual Review of Psychology* 53(1): 1–25.

van de Ven, Vincent, Moritz Jäckels, and Peter De Weerd. 2021. "Time Changes: Timing Contexts Support Event Segmentation in Associative Memory." *Psychonomic Bulletin & Review* .

Van Kesteren, Marlieke T.R., Dirk J. Ruiter, Guillén Fernández, and Richard N. Henson. 2012. "How Schema and Novelty Augment Memory Formation." *Trends in Neurosciences* 35(4): 211–219.

Wang, Jingyi, Arielle Tambini, and Regina C. Lapate. 2022. "The Tie That Binds: Temporal Coding and Adaptive Emotion." *Trends in Cognitive Sciences* 26(12): 1103–1118.

Wang, Yuxi Candice, and Tobias Egner. 2022. "Switching Task Sets Creates Event Boundaries in Memory." *Cognition* 221: 104992.

Watson, David, Lee Anna Clark, and Auke Tellegen. 1988. "Development and Validation of Brief Measures of Positive and Negative Affect: The PANAS Scales." *Journal of Personality and Social Psychology* 54(6): 1063–1070.

Wen, Tanya, and Tobias Egner. 2022. "Retrieval Context Determines Whether Event Boundaries Impair or Enhance Temporal Order Memory." *Cognition* 225: 105145.

Wu, Xiongbo, Pau A. Packard, Josué García-Arch, Nico Bunzeck, and Lluís Fuentemilla. 2023. “Contextual Incongruency Triggers Memory Reinstatement and the Disruption of Neural Stability.” *NeuroImage* 273: 120114.

Yates, Tristan S., Brynn E. Sherman, and Sami R. Yousif. 2023. “More Than a Moment: What Does It Mean to Call Something an ‘Event’?” *Psychonomic Bulletin & Review* 30(6): 2067–2082.

Yazin, Fahd, Moumita Das, Arpan Banerjee, and Dipanjan Roy. 2021. “Contextual Prediction Errors Reorganize Naturalistic Episodic Memories in Time.” *Scientific Reports* 11(1): 12364.

Yonelinas, Andrew P., Charan Ranganath, Arne D. Ekstrom, and Brian J. Wiltgen. 2019. “A Contextual Binding Theory of Episodic Memory: Systems Consolidation Reconsidered.” *Nature Reviews Neuroscience* 20(6): 364–375.

Zacks, Jeffrey M. 2004. “Using Movement and Intentions to Understand Simple Events.” *Cognitive science* 28(6): 979–1008.

Zacks, Jeffrey M. 2019. “Event Perception and Memory.” *Annual review of psychology* 71(1): 29–58.

Zacks, Jeffrey M., and Barbara Tversky. 2001. “Event Structure in Perception and Conception.” *Psychological Bulletin* 127(1): 3–21.

Zacks, Jeffrey M., and Khena M. Swallow. 2007. “Event Segmentation.” *Current Directions in Psychological Science* 16(2): 80–84.

Zacks, Jeffrey M., Barbara Tversky, and Gowri Iyer. 2001. “Perceiving, Remembering, and Communicating Structure in Events.” *Journal of Experimental Psychology: General* 130(1): 29–58.

Zacks, Jeffrey M., Christopher A. Kurby, Michelle L. Eisenberg, and Nayiri Haroutunian. 2011. “Prediction Error Associated with the Perceptual Segmentation of Naturalistic Events.” *Journal of Cognitive Neuroscience* 23(12): 4057–4066.

Zacks, Jeffrey M., Nicole K. Speer, and Jeremy R. Reynolds. 2009. “Segmentation in Reading and Film Comprehension.” *Journal of Experimental Psychology: General* 138(2): 307–327.

Zacks, Jeffrey M., Nicole K. Speer, Khena M. Swallow, Todd S. Braver, and Jeremy R. Reynolds. 2007. “Event Perception: A Mind-Brain Perspective.” *Psychological Bulletin* 133(2): 273–293.

APPENDIX A

A.1 Part 1: Underlying Mechanisms of Event Segmentation

Response times (RT) and confidence judgments were provided in the supplementary materials due to space constraints.

A.1.1 Experiment 1

Confidence judgments for temporal order judgments were lower for across-event pairs (M = .65, SD = .18) than within-event pairs (M = .69, SD = .16), BF10 = 46.18. RT in order judgments were higher for across-event pairs (M = 3.49, SD = 1.35) compared to within-event pairs (M = 3.38, SD = 1.23), with anecdotal evidence, BF10 = 1.80 (Supplementary Figure 1A & 2A). There was anecdotal evidence for equal temporal distance judgment RT for within-event (M = 1.48, SD = .38) and across-event pairs (M = 1.45, SD = .34), BF01 = 1.54 (Supplementary Figure 3A). Moreover, there was moderate evidence for indifference in temporal distance confidence judgments between within-event pairs (M = .70, SD = .26) and across-event pairs between item pairs (M = .67, SD = .26), BF01 = 3.11 (Supplementary Figure 4A).

A.1.2 Experiment 2

Confidence judgments for order judgments were higher for within-event (M = .69, SD = .15) compared to across-event pairs (M = .66, SD = .14), with anecdotal evidence, BF10 = 1.75 (Supplementary Figure 2B). RTs during order judgments were higher for across-event pairs (M = 3.98, SD = 1.46) compared to within-event pairs (M = 3.70, SD = 1.40), BF10 = 60.55 (Supplementary Figure 1B). Confidence judgments for temporal distance were higher for within-event pairs (M = .72, SD = .18) than across-event pairs (M = .69, SD = .21), with anecdotal evidence, BF10= 1.19 (Supplementary Figure 4B). There was substantial evidence for the indifference of RTs for temporal distance judgments for within (M = 1.65, SD = .50) and across-event pairs (M = 1.66, SD = .48), BF01 = 3.14 (Supplementary Figure 3B).

A.1.3 Comparison between Experiments 1 & 2

For the comparison between Experiment 1 and 2, the event segmentation score (within- minus across-event scores) for temporal order RTs was higher for Experiment 2 (M = .27, SD = 45) than for Experiment 1 (M = .11, SD = .32), with anecdotal evidence, BF10 = 1.38. There was indifference between experiments for confidence judgments for temporal order (BF01 = 2.35), temporal distance RTs (BF01 = 1.92), and confidence judgments for temporal distance judgments (BF01 = 2.40), with anecdotal evidence.

A.1.4 Experiment 3

The measures were evaluated for the prediction error blocks. There was no evidence for the difference between within and across-pairs for RT in temporal order memory (BF10 = 0.15), confidence judgments in temporal order memory (BF10 = 0.22), RTs for temporal distance judgments (BF10 = 0.15), and confidence judgments for temporal distance judgments (BF10 = 0.38). For the contextual stability blocks, RTs in temporal order memory were higher for across-event pairs (M = 4.61, SD = 4.16) than within-event pairs (M = 3.85, SD = 2.42), BF10 = 3.95. Confidence judgments for within-events (M = .73, SD = .15) were higher than across-event pairs (M = .64, SD = .18) in temporal order with strong evidence, BF10 = 567.31. Confidence judgments for temporal distance judgments were higher for within-events (M = .73, SD = .23) than across-events (M = .67, SD = .25), with strong evidence, BF10 = 23.58. There was no evidence for the difference between across and within-event pairs' RTs for temporal distance judgments (BF10 = .41).

We compared the difference scores for each measure between conditions. RTs for temporal order indicated higher segmentation in contextual stability (M = .76, SD = 2.07) than prediction error blocks (M = .02, SD = 1.60), with anecdotal evidence, BF10 = 2.26. Confidence judgments for temporal order generated higher segmentation for contextual stability (M = .08, SD = .13) than prediction error (M = .01, SD = .10), with substantial evidence, BF10 = 7.02. RTs (BF10 = .22) and confidence judgments (BF10 = 0.60) for temporal distance judgments were not differentiated between conditions.

A.1.5 Experiment 4

For the predictable blocks, RTs were higher during within-event (M = 3.16, SD = 1.00) than across-event pairs (M = 3.53, SD = 1.38) for temporal order memory, BF10 = 151.90. Confidence judgments for within-event pairs (M = .68, SD = .19) were higher than across-event pairs (M = .60, SD = .21) for temporal order memory, BF10 = 192.04. Similarly, confidence judgments for within-event pairs (M = .69, SD = .25) were higher than across-event pairs (M = .63, SD = .29) for temporal distance memory, BF10 = 113.09. There was no evidence for the difference between within and across-event pairs for RTs for temporal distance judgments (BF10 = .16).

For the unpredictable blocks, RTs were higher for across (M = 3.63, SD = 1.51) than within-event pairs (M = 3.35, SD = 1.23) for temporal order memory, BF10 = 4.05. Confidence judgments were higher for within-event pairs (M = .69, SD = .19) than across-event pairs (M = .57, SD = .21) for temporal order memory, BF10 = 159250. Similarly, confidence judgments were higher for within-event pairs (M = .69, SD = .24) than across-event pairs (M = .64, SD = .27) for temporal distance judgments, BF10 = 32.82. There was no evidence for the difference between within and across-event pairs for RTs for temporal distance judgments (BF10 = .20)

We compared the difference scores for each measure between conditions. There was no evidence for the difference in segmentation scores between variables (BF10 ≥ .13).

Figure A.1 Temporal order memory RTs for within and across-event pairs in Experiment 1 and Experiment 2.

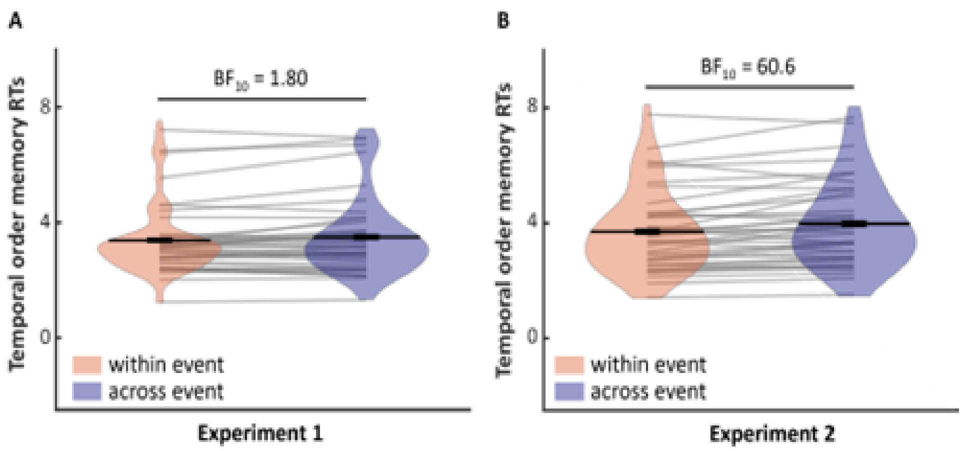


Figure A.2 Temporal order memory confidence judgments for within and across-event pairs in Experiment 1 and Experiment 2.

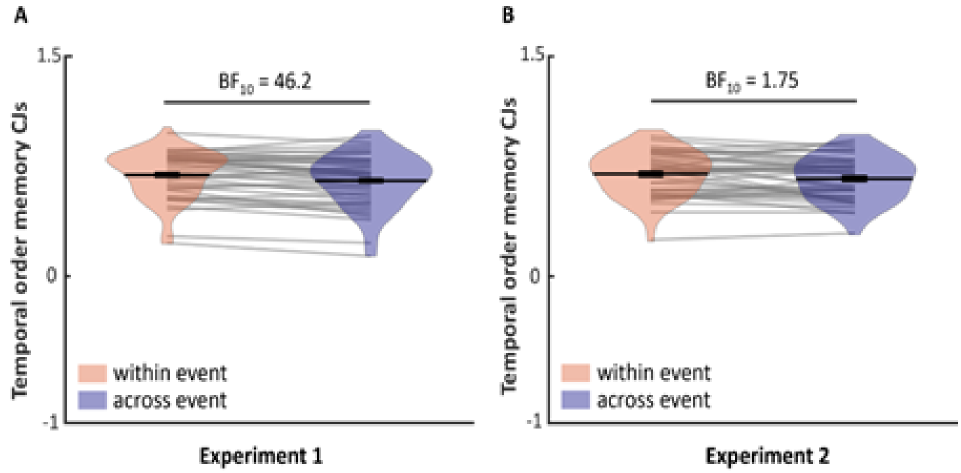


Figure A.3 RTs for temporal distance judgments for within and across-event pairs in Experiment 1 and Experiment 2.

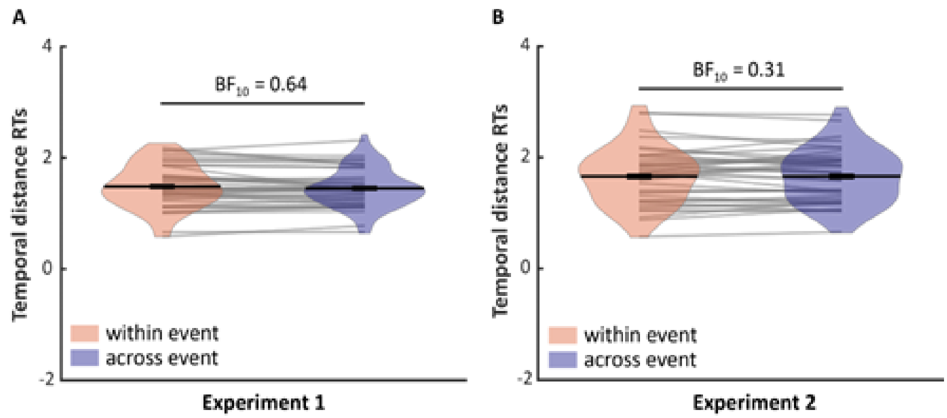


Figure A.4 Confidence judgments for temporal distance judgments for within and across-event pairs in Experiment 1 and Experiment 2.

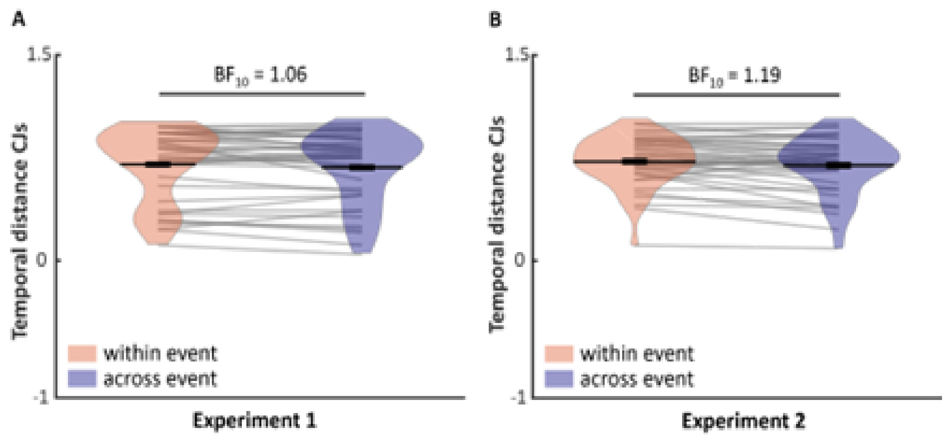


Figure A.5 Temporal order memory accuracy for within and across-event pairs between Experiments 1 and 2.

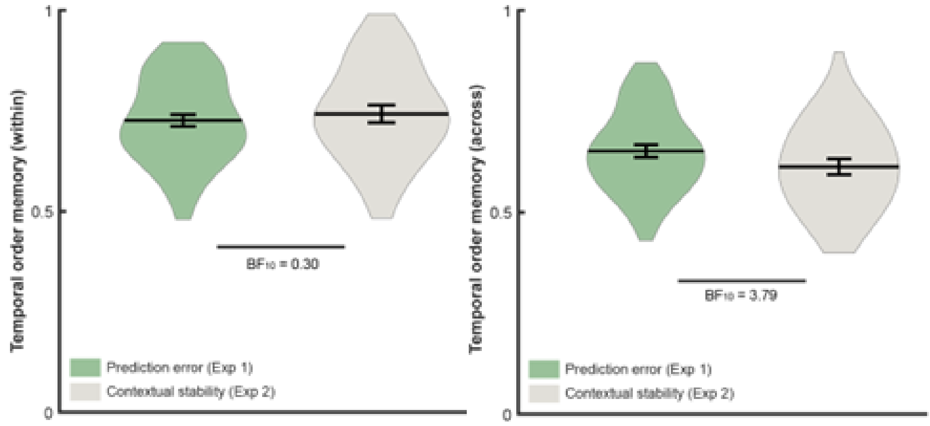


Figure A.6 Temporal order memory accuracy for within and across-event pairs between conditions for Experiment 3.

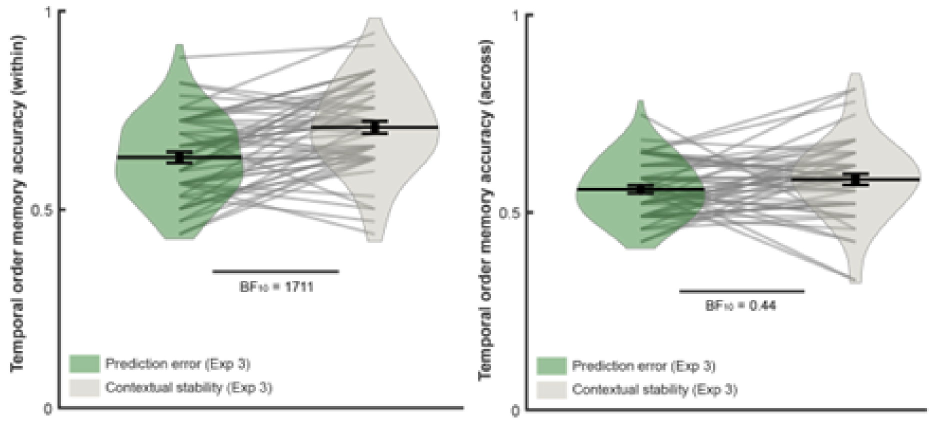


Figure A.7 Temporal order memory RTs for prediction error and contextual stability blocks in Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions.

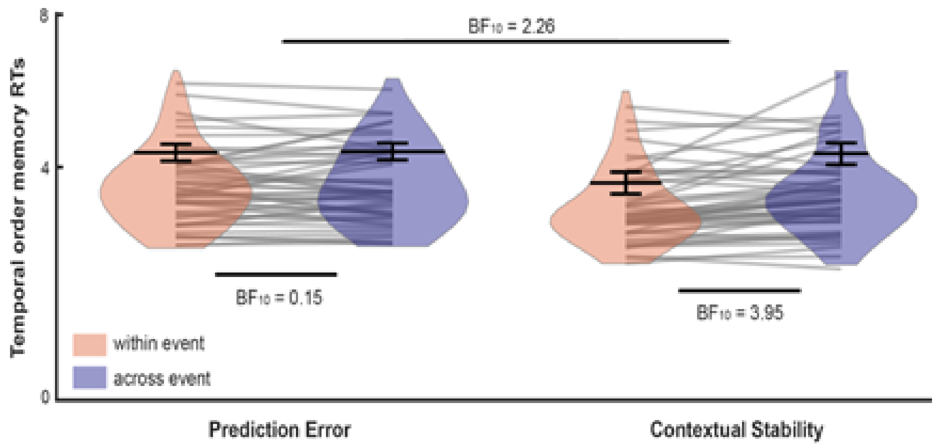
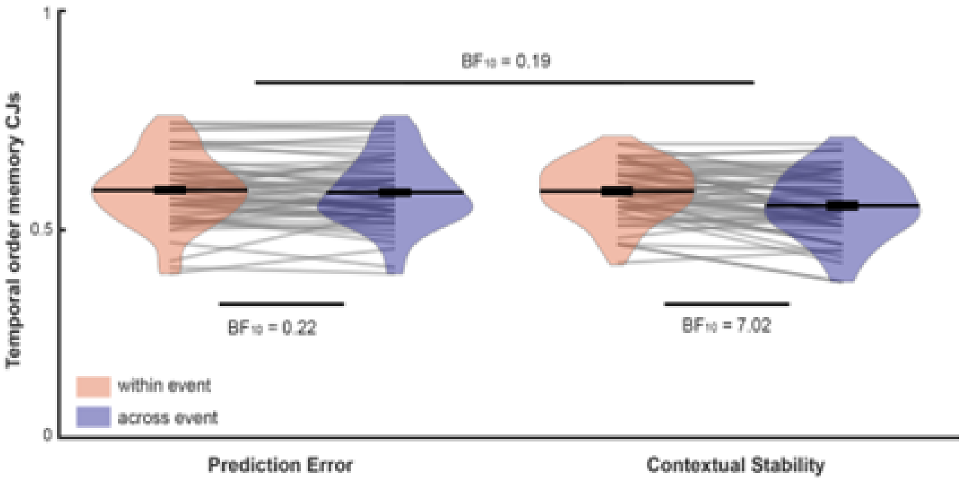


Figure A.8 Temporal order memory confidence judgments for prediction error and contextual stability blocks in Experiment 3. The Bayes Factor above reflects the comparison of the segmentation scores (within-across difference) across conditions.



APPENDIX B

B.1 Part 2: Online Effects of Reward on Event Segmentation

B.1.1 Experiment 1

RTs for temporal order were higher for across-event (M = 4.10, SD = 1.76) than within-event pairs (M = 3.57, SD = 1.22), with strong evidence, BF10 = 81.1. For high-rewarded transitions, RTs for temporal order were higher for across-event (M = 4.06, SD = 1.87) than within-event pairs (M = 3.64, SD = 1.24), with anecdotal evidence, BF10 = 1.75. For low-rewarded transitions, RTs for temporal order were higher for across-event (M = 4.14, SD = 1.76) than within-event pairs (M = 3.50, SD = 1.27), with strong evidence, BF10 = 384.

Confidence judgments for temporal order were higher for within-event (M = .69, SD = .13) than across-event pairs (M = .59, SD = .16), with strong evidence, BF10 = 575. For high-rewarded transitions, confidence judgments for temporal order were higher for within-event (M = .69, SD = .14) than across-event pairs (M = .58, SD = .16), with strong evidence, BF10 = 86. For low-rewarded transitions, confidence judgments for temporal order were higher for within-event (M = .69, SD = .15) than across-event pairs (M = .60, SD = .19), with strong evidence, BF10 = 23.8.

There was an indifference between RTs for the temporal distance between across-event (M = 1.44, SD = .47) and within-event pairs (M = 1.42, SD = .45), with moderate evidence, BF01 = 4.48. For high-rewarded transitions, there was an indifference between RTs for the temporal distance between across-event (M = 1.46, SD = .48) and within-event pairs (M = 1.43, SD = .44), with moderate evidence, BF01 = 4.05. For low-rewarded transitions, there was an indifference between RTs for the temporal distance between across-event (M = 1.42, SD = .49) and within-event pairs (M = 1.41, SD = .48), with moderate evidence, BF01 = 4.99.

Confidence judgments for temporal distance were higher for within-event (M = .69, SD = .20) than across-event pairs (M = .63, SD = .21), with strong evidence, BF10 = 40.5. For high-rewarded transitions, confidence judgments for temporal distance were higher for within-event (M = .70, SD = .20) than across-event pairs (M = .64, SD = .21), with moderate evidence, BF10 = 4.64. For low-rewarded transitions, confidence judgments for temporal distance were higher for within-event (M = .68, SD = .21) than across-event pairs (M = .62, SD = .24), with anecdotal evidence, BF10 = 2.99.

B.1.2 Experiment 2

RTs for temporal order were higher for across-event (M = 3.94, SD = 1.86) than within-event pairs (M = 3.68, SD = 1.59), with strong evidence, BF10 = 25.9. For high-rewarded transitions, there was indifference between RTs for temporal order across-event (M = 4.06, SD = 1.87) and within-event pairs (M = 3.64, SD = 1.24), with anecdotal evidence, BF01 = 1.99. For low-rewarded transitions, RTs for temporal order were higher for across-event (M = 3.98, SD = 2.07) than within-event pairs (M = 3.61, SD = 1.69), with strong evidence, BF10 = 39.1.

Confidence judgments for temporal order were higher for within-event (M = .68, SD = .14) than across-event pairs (M = .59, SD = .15), with strong evidence, BF10 = 95009. For high-rewarded transitions, confidence judgments for temporal order were higher for within-event (M = .68, SD = .14) than across-event pairs (M = .58, SD = .18), with strong evidence, BF10 = 73778. For low-rewarded transitions, confidence judgments for temporal order were higher for within-event (M = .68, SD = .16) than across-event pairs (M = .60, SD = .15), with strong evidence, BF10 = 106.

RTs for the temporal distance were higher for within-event (M = 1.63, SD = .64) than across-event pairs (M = 1.56, SD = .70), with anecdotal evidence, BF01 = 1.71. For high-rewarded transitions, there was an indifference between RTs for the temporal distance between across-event (M = 1.55, SD = .69) and within-event pairs (M = 1.63, SD = .64), with anecdotal evidence, BF01 = 1.83. For low-rewarded transitions, there was an indifference between RTs for the temporal distance between across-event (M = 1.58, SD = .76) and within-event pairs (M = 1.64, SD = .68), with anecdotal evidence, BF01 = 2.16.

Confidence judgments for temporal distance were higher for within-event (M = .66, SD = .22) than across-event pairs (M = .61, SD = .23), with strong evidence, BF10 = 161. For high-rewarded transitions, confidence judgments for temporal distance were higher for within-event (M = .67, SD = .21) than across-event pairs (M = .62, SD = .24), with strong evidence, BF10 = 109. For low-rewarded transitions, confidence judgments for temporal distance were higher for within-event (M = .64, SD = .25) than across-event pairs (M = .60, SD = .24), with moderate evidence, BF10 = 5.72.

APPENDIX C

C.1 Part 3: Retrospective Effects of Emotion Regulation on Event Segmentation

The correlation table can be seen in Figure C.1

Figure C.1 Correlation matrix for individual difference measures and segmentation scores.

	TO_reap	TO_view	TO_think	TD_reap	TD_view	TD_think	PANAS_pos	PANAS_neg	ERQ_reap	ERQ_supp	PINTS_sum	STAI_state	STAI_trait	DERS	BDI	PCL
TO_reap	—															
TO_view	-.04	—														
TO_think	-.20	.02	—													
TD_reap	-.23	-.31*	.18	—												
TD_view	-.14	.04	.04	.10	—											
TD_think	.00	-.01	-.03	-.12	.26	—										
PANAS_pos	-.02	-.23	-.13	.20	-.13	-.13	—									
PANAS_neg	.00	-.05	.35*	-.16	-.03	.02	0.13	—								
ERQ_reap	-.09	-.22	-.08	.02	-.05	-.07	0.21	-.22	—							
ERQ_supp	.12	-.28	-.08	.04	-.04	.02	0.07	.29*	-.03	—						
PINTS_sum	-.19	.08	.31*	-.17	-.04	-.05	-0.04	.55***	-.23	.11	—					
STAI_state	.09	-.02	.22	-.13	-.03	.05	-0.22	.71***	-.41**	.26	.43***	—				
STAI_trait	.10	-.00	.2	-.22	.05	-.03	-0.21	.50***	-.31*	.25	.51***	.67***	—			
DERS	-.07	-.00	.22	-.11	-.01	-.02	-0.02	.51***	-.31*	.28	.58***	.50***	.73***	—		
BDI	.07	-.02	.19	-.16	-.00	.14	-0.23	.52***	-.33*	.28	.47***	.68***	.80***	.59***	—	
PCL	-.10	.02	.15	-.13	-.15	-.11	0	.54***	-.10	.20	.62***	.49***	.69***	.62***	.67***	—

Note. * $p < .05$, ** $p < .01$, *** $p < .001$