THE ROLE OF WORKING MEMORY ON EVENT SEGMENTATION

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ABSTRACT

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Event segmentation is known as the process of mentally partitioning continuous episodic events into meaningful units. It allows related information, that is grouped into an event, to be recalled better compared to information across different events. However, the role of working memory (WM) in this process remains relatively unexplored. Based on existing studies, we collected contrasting views about the role of WM on segmentation under two accounts: Accumulation, where memoranda are claimed to be accumulated until an event boundary, and Reactivation, where each memorandum is claimed to be transferred to Long-Term Memory (LTM) and is reactivated once there is an event boundary. Here, we challenged these accounts in a single EEG study, using a direct measure of WM capacity, Contralateral Delay Activity (CDA), and a sensitive measure of attentional involvement, Bilateral Alpha Power. We have found a significant systematic increase in CDA within main events, which supports the Accumulation account by reflecting the increase in WM capacity throughout memoranda within a main event. We also found a higher bilateral alpha suppression during the beginning of boundary events compared to the beginning of main events, which reflects the increased activation of WM representations, endorsing the claims of the Reactivation account. Our findings suggest that these claims do not have to be mutually exclusive. By co-existing, they may reflect the dynamic nature of the relationship between WM and event segmentation, expanding the scope of research on cognitive psychology.

ÖZET

ÇALIŞAN BELLEĞIN OLAY SEGMENTASYONUNDAKI ROLÜ

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PSİKOLOJİ YÜKSEK LİSANS TEZİ, ARALIK 2023

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Anahtar Kelimeler: çalışan bellek, olay segmentasyonu, olay sınırı, olaysal bellek, kontralateral tutulma aktivitesi

Olay segmentasyonu ("event segmentation"), süreğen bir akış içerisinde deneyimlediğimiz olayları zihinsel olarak anlamlı birimlere ayırma süreci olarak bilinir. Ancak çalışan belleğin bu süreçteki rolüne nispeten çok ışık tutulmamıştır. Mevcut çalışmalara dayanarak, çalışan belleğin segmentasyondaki rolü hakkındaki görüşleri iki model altında topladık: Bilgilerin bir olay sınırıyla karşılaşıncaya kadar çalışan bellekte biriktirildiğini iddia eden Birikim ("Accumulation") Modeli ve bir olay içindeki her bilginin önce uzun süreli belleğe aktarılıp, ancak bir olay sınırıyla karşılaşıldığında çalışan bellekte topluca aktive edildiğini iddia edilen Yeniden Etkinleştirme ("Reactivation") Modeli. Bu modelleri tek bir EEG çalışmasında çalışan bellek kapasitesinin doğrudan bir ölçüsü olan Kontralateral Tutulma Aktivitesi ("CDA") ve dikkatin hassas bir ölçüsü olan Çift Taraflı Alfa Gücü'nü ("Bilateral Alpha Power") kullanarak test ettik. Ana olaylarda Kontralateral Tutulma Aktivitesinde önemli bir sistematik artış tespit ettik; bu, bir ana olay boyunca çalışan bellekte tutulan bilgilerin sayısını yansıttığı için Birikim modelini desteklemektedir. Ayrıca, ana olayların başlangıcına kıyasla sınır olaylarının başlangıcında daha yüksek çift taraflı alfa baskılanması bulduk; bu, çalışan bellekteki bilgilerin bir olay sınırı ile birlikte aktive edildiğini gösterdiği için Yeniden Aktivasyon modelini desteklemektedir. Bulgularımız, bu modellerin karşılıklı dışlayan modeller olmadığını gösteriyor. Aksine, bir arada var olarak, çalışan bellek ile olay segmentasyonu arasındaki ilişkinin dinamik doğasını yansıtıyor ve bilişsel psikoloji üzerine yapılan araştırmaların kapsamını genişletici bir potansiyel taşıyorlar.

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My beautiful mother, Selma, Everyone gets a chance in this world, and I believe I used mine the moment I was born as your daughter. You are the smartest, most knowledgeable, foresighted, and compassionate woman I have ever known. You have the biggest, kindest heart I have ever felt. I owe you the world for teaching me how to live, learn, question, and, most importantly, love. You are the most special teacher in my life and my best friend as well. Wherever life takes me, I will carry your love in my heart. Thank you for being the incredible person you are.

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Dedication page

Dedicated to the woman who I aspire to be, my loving mother, Selma.

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1. GENERAL INTRODUCTION

We collect many different memories throughout the day. Even the smallest moments that are usually considered ordinary, such as preparing coffee first thing in the morning, conversations with a colleague during short breaks, or meeting with our friends, turn into various chunks of memories at the end of the day. However, no matter how small it is, no memory is isolated; all the moments we collect during the day are processed one by one into episodic memory.

Episodic memory is part of a bigger memory system, that is long-term memory (LTM), and it enables us to preserve, organize, and retrieve personal experiences and memories (Tulving 1993; Tulving 2002). Yet, a question arises: How can all these continuous memories we experience throughout the day be stored in the episodic memory? The answer is, that even though it seems like a continuous experience at the time, we tend to remember it in fragments later on such as picking an outfit, leaving the house, taking the subway, arriving at work, and meeting with our friends afterward. This intricate process of mentally segmenting continuous episodic events into meaningful units is due to a phenomenon called event segmentation (Zacks and Swallow 2007; Kurby and Zacks 2008). Event segmentation facilitates the organization, encoding, and retrieval of episodic memories in which related information, that is grouped into an event, is recalled better compared to information across different events (Sargent et al. 2013; Shin and DuBrow 2021). It contributes to prioritizing information about the current event while making it difficult to access the previous events (Radvansky and Copeland 2006; Radvansky, Krawietz and Tamplin 2011; Horner et al. 2016). Thus, it can be seen as a fundamental building block of information processing and memory formation.

Each segmented event is separated by event boundaries, which are mental tags that mark the end of an event and the beginning of another. It is possible to mention two main proposed mechanisms regarding the formation of event boundaries. According to the Event Segmentation Theory (EST), working memory (WM) is claimed to play an essential role in event segmentation. Specifically, WM is suggested to maintain event models, which are defined as the active mental representations of experiences. Event models store the contents of currently experienced information, which are used for making predictions about what is expected to happen next (Speer, Zacks and Reynolds 2007; Swallow, Zacks and Abrams 2009; Zacks and Swallow 2007). When the predictions are not in line with upcoming events, the prediction error occurs and thus, the boundaries are triggered to create a new event model. To clarify, the prediction error account, the second mechanism, argues that we form an event model that represents the current experience, use this model to forecast what might happen next and whenever the incoming experience does not fit our current event model, we create a new one.

The second of these, the Contextual Stability Account, proposes that event boundaries are formed due to expected disruptions in stable and coherent contexts (Güler, Serin and Günseli 2023; DuBrow and Davachi 2016; Wang and Egner 2022). Some ways of creating stable contexts include the permanence of object categories (DuBrow and Davachi 2016), goal-directed rules (Wang and Egner 2022), consistent narratives (Ezzyat and Davachi 2011), or probe durations (Heusser et al. 2018). Segmentation occurs when contextual stability is disrupted by various physical or conceptual changes during perception.

Although the exploration regarding the underlying mechanisms of event segmentation is fairly crowded, comparing these two main accounts was less saturated within the literature. However, in a recent study done by Güler et al. (2023), contextual stability and prediction error accounts were compared and contrasted on which one had a more prominent effect on the segmentation of events. During encoding, participants had to watch a series of different category images and make goal-directed estimates. In the first experiment that induced prediction error, one category of items was deviant since it required a different type of estimate, was rewarded, and only occurred once in every 6 items. In the second experiment that introduced contextual stability, each event contained 6 items, and a task rule and was rewarded either low or high, thus being more consistent overall. During the test phase, the event segmentation score was measured based on participants' performance on temporal judgment and order of these items. Their study revealed that inducing contextual stability resulted in better event segmentation performance and therefore was a more dominating factor in event segmentation compared to prediction errors.

2. THE ROLE OF WM ON EVENT SEGMENTATION

Even though the influential models of event segmentation, such as Event Segmentation Theory, propose that instances of an ongoing event are stored in WM, to date, there is only limited evidence to support this claim. For example, in a functional magnetic resonance imaging (fMRI) study, Ezzyat and Davachi (2011) observed a gradual increase of activity in the ventromedial PFC (vmPFC) during the encoding of sentences from one to six when participants read narratives that contain temporal event boundaries. Given the role of PFC in holding task-related information in WM (Goldman-Rakic 2011; Miller and Cohen 2001; Baddeley 2003), the vmPFC activity increase within an event can be considered as evidence for the accumulation of memoranda in WM until an event boundary. However, this conclusion is based on reverse inference. An increase in vmPFC activity may instead reflect a greater effort to integrate the current content with previously encoded information. Since the amount of previously encoded information also increases within an event, this explanation would be consistent with the possibility that these contents are not accumulated in WM but rather already transferred to LTM. Additional support for the Event Segmentation Theory comes from behavioral studies where participants go through a slide show at their own pace. For example, in one such study, looking time at the slides gradually increased and peaked at event boundaries (Hard, Recchia and Tversky 2011; Kosie and Baldwin 2019). Here too, increased cognitive demands of forming associations between parts of memoranda within an event can explain why looking times increase. Not all memoranda that are part of forming associations need to be accumulated in WM as suggested by the Event Segmentation Theory. In short, increased neural activity or slowing down towards an event boundary does not provide deterministic evidence for the accumulation of information within an event in WM.

The accumulation argument of Event Segmentation Theory does not only have merely indirect support but also has counter-evidence against it. This line of evidence comes from recent studies that claim information is reactivated in WM at an event boundary. Moreover, such reactivation is not observed before a boundary, which implies that information has not been accumulated in WM until an event boundary. In one such study, Sols and colleagues (2017) measured participants' brain activity via electroencephalography (EEG) while presenting a sequence of visual stimuli in which event boundaries are formed by category changes. They found that EEG activity patterns that are observed during the perception of memory items within an event were reinstated at event boundaries. Similar EEG results were obtained by Silva, Baldassano and Fuentemilla (2019), where a rapid reactivation of the previous event at boundaries was observed while participants were watching a movie. Moreover, an fMRI study observed that the neural traces of an ongoing story were reactivated at storyline transitions while participants read a story with sudden context changes (Chang et al. 2021). These studies suggest that when an event boundary is encountered, memories of the preceding event, which have not been active until then, are reactivated and processed in WM. These studies are against the aforementioned accumulation account that proposes information is accumulated in WM until an event boundary because, in these studies, the reactivation was specific to event boundaries. If information has been accumulated in WM throughout the event as suggested by the accumulation framework of the Event Segmentation Theory, then reading out all items should have been possible before event boundaries.

Together, these findings highlight two contrasting views regarding the role of WM in event segmentation. First, information within an event is suggested to be accumulated in WM until encountering an event boundary (Clewett and Davachi 2017; Ongchoco and Scholl 2019; Ezzyat and Davachi 2011; Hard et al. 2011). We will refer to this view as the accumulation account. Second, information that is recently encountered is handed off to LTM, reserving WM for only the most recent information. Only at an event boundary, the contents that have been previously handed off to LTM are reactivated in WM (Chang et al. 2021; Silva et al. 2019; Sols et al. 2017). We will refer to this view as the reactivation account.

To reconcile these contrasting views, here, we used a direct measure of WM load, the Contralateral Delay Activity (CDA). The CDA is sustained negativity at the parietal-occipital electrodes that are contralateral to the position of target stimuli (Gunseli, Meeter and Olivers 2014; Gunseli et al. 2019; Adam, Robison and Vogel 2018; Becke et al. 2015) that is sensitive to the number of items stored in WM (Vogel and Machizawa 2004; Vogel, McCollough and Machizawa 2005; Luria et al. 2016). Due to its sensitive nature, the CDA enabled us to observe how many items were kept in WM, therefore testing the accumulation account. On the other hand, we also calculated bilateral alpha suppression. Bilateral alpha power represents the oscillations of alpha waves, which are characterized by a relaxed state (beim Graben and Kurths 2008). Increased suppression of these oscillations represents a greater effort to attend and maintain WM representations (Gunseli et al. 2018; Gunseli et al. 2019; Riddle et al. 2020), higher cognitive engagement (Williamson et al. 1997), and mental imagery (Kaufman et al. 1990). Therefore, using bilateral alpha suppression allowed testing the reactivation account, as the extent to which alpha oscillations were suppressed at certain periods would indicate that previously encoded items were being reactivated.

Individuals saw a series of pictures of inanimate (e.g., tools, vehicles, foods, etc) and animate objects (animals). Moreover, they heard a category-specific sound with each image, such that inanimate objects were accompanied by sounds that resembled city life whereas animate objects appeared with nature sounds. To create event boundaries, we switched the category of pictures and sounds between each main and boundary event. (Heusser et al. 2018; van de Ven, Jäckels and De Weerd 2022). After 24 images, we behaviorally assessed event segmentation, using temporal order memory (DuBrow and Davachi 2013; DuBrow and Davachi 2014; van de Ven et al. 2022) and sequential memory tasks (Sols et al. 2017). In the temporal order memory task, participants were shown two images and were instructed to indicate which image appeared earlier in the study phase. In the sequential memory task, we presented an image and instructed participants to recall the category of the following image in the study phase. We predicted if changes in object and sound categories result in event segmentation, responses would be faster or more accurate for within-event image pairs compared to across-event pairs for each task (van de Ven et al. 2022; DuBrow and Davachi 2013; DuBrow and Davachi 2014; Sols et al. 2017).

The aforementioned claims of WM functioning for event segmentation make distinct predictions of how information is kept in WM, thus reflected in both the bilateral alpha suppression and CDA amplitude. According to the accumulation account, memory items within an event should accumulate in WM, which predicts a gradual increase in CDA amplitude until an event boundary. This increase would start around the second item of a main event, taking into consideration that the first item would have no accumulation. According to the reactivation account, information is handed off to LTM immediately after the initial encounter and is reactivated at an event boundary, which predicts a lower alpha suppression during the first item of the main event and a higher alpha suppression during the first item of the boundary event, reflecting the mental reactivation of items before the boundary event. The reason for that prediction is that the number of items needed to be reactivated would be much lower at the beginning of a main event, compared to the beginning of boundary events, which are followed by 6-item main events.

The rationale for using the CDA to test only the accumulation account lies within its distinct characteristics. The CDA is a sensitive measure of WM capacity. However, the reactivation account claims that the items are not actively stored in WM, but are rather reactivated in WM once there is an event boundary. Therefore, instead of using CDA, we decided to implement a better measure that is known to reflect active WM representations of items, which is alpha-band power. Thus, by using a direct electrophysiological marker of WM storage (i.e., the CDA) and alpha-band power, this study explored the role of WM in event segmentation.

2.1 Method

2.1.1 Participants

To calculate the minimum number of participants needed, we conducted a power analysis that calculates 95% power for paired samples t-test (α = .05). The analysis revealed that a minimum of 22 participants were needed for the study. Therefore we collected data from 32 participants that are between the ages of 18 to 26 from Sabancı University in exchange for course credit. All participants were given an informed consent form prior to participating in the study and asked to sign it. Due to the ocular and recording artifacts, the data from 9 subjects were excluded, leaving 23 participants (15 female; *M* = 21.4, *SD* = 1.83) for final analyses. All participants had normal or corrected-to-normal vision, and they had no reported history of neuropsychological disorders.

2.1.2 Ethics Statement

This study is performed according to the Declaration of Helsinki principles and the ethics approval was granted by the Sabancı University (SUREC) ethics committee.

2.1.3 Stimuli

A set of 1068 real-life images (Google Images; Konkle et al. 2010; Konkle and Oliva 2012; Konkle and Caramazza 2013) were resized to an approximately equal number of non-transparent pixels and were divided into two sets: 540 target and 528 non-target stimuli. Both sets were grouped into two categories in terms of their living status (animate and inanimate). Both target and non-target objects appeared only once in the approximately first half of the blocks, then randomly selected and reappeared once again in the remaining blocks.

An additional 6 category-specific sounds were presented simultaneously with the respective object categories for both animate and inanimate categories.

The experiment is programmed in MATLAB (Mathworks). The viewing distance to the screen was approximately 85 cm and the background color for the experiment was grey. The location cue was a vertically halved, bicolored circle (0.35° x 0.35°), with one side being navy blue and the other side being orange. The location cue represented where the target stimulus would appear in a particular color and it was counterbalanced across blocks and participants. The target and non-target objects were equidistant from the location cue.

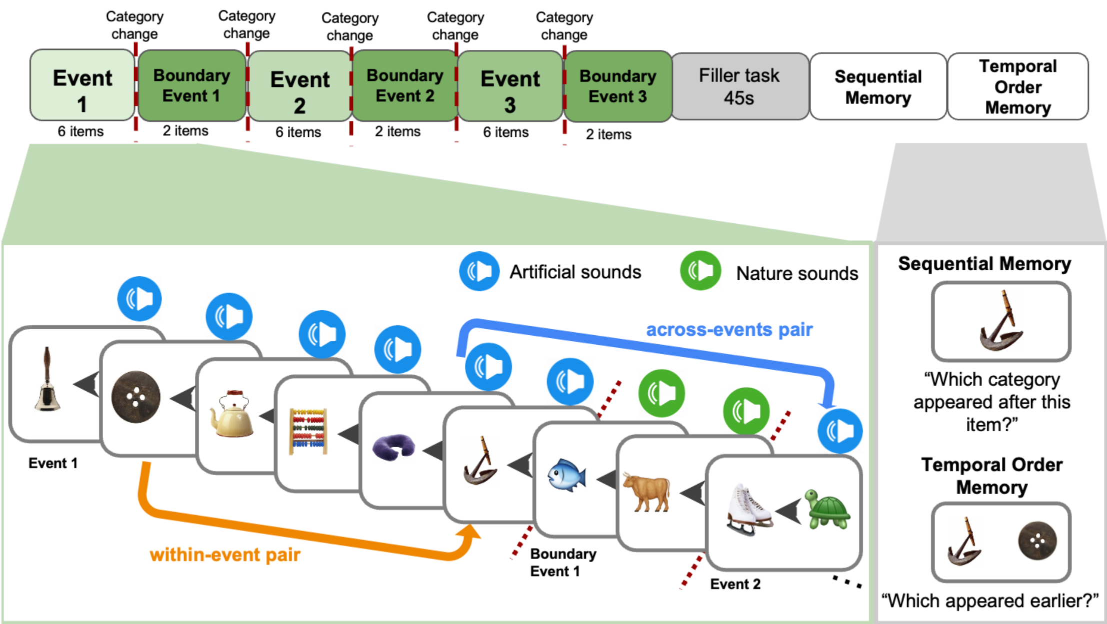
2.2 Design and Procedure

2.2.1 Trial Design

2.2.1.1 Phase 1 - encoding (study phase)

The block structure for the experiment is depicted in Figure 1. Before starting, participants completed a practice round and proceeded only when they reached a minimum of 50% accuracy in behavioral tests. In the main study, each block consisted of a study and test phase, and each study phase started with a location cue presented in the middle of the screen for a randomly jittered duration of 800-1200 ms. Next, two images were presented on each side of the location cue for 2 seconds. Participants were instructed to memorize the target image on the cued side of the screen and ignore the other image. The first target image was selected to be either animate or inanimate based on whether the subject and the trial number were odd or even, and was counterbalanced across participants. The following target images were also from the same category. Between each image, there was a 1-second interstimulus interval. I will refer to a series of 6 within-category images as a main event throughout the thesis. Each image within a main event was accompanied by a category-specific sound. For example, if the main event consisted of animate images, the category-specific sounds were nature sounds; specifically the sounds of a lakeside, jungle, and farm. Likewise, inanimate images were accompanied by office and traffic sounds. Thus, for each main event, both the visual and auditory stimuli belonged to either an animate or an inanimate category. The goal of this approach was to facilitate event segmentation. The sound duration matched the duration of the visual presentation of the objects. After a main event ended, a new boundary event would start with a different target category following a jittered duration of 800-1200 ms. Boundary events, on the other hand, consisted of two target images but accompanied by non-target images with the opposite side of the location cue, and a category-specific sound, similar to main events. Within each block, there were 3 main and 3 boundary events that each were presented with a different sound, and in total 24 target images. The category of non-target images also matched the category of target images throughout the experiment to further facilitate segmentation.

Figure 2.1 The experimental procedure



2.2.1.2 Phase 2 - filler task

Before the test phase, participants were asked to perform a 54-second-long change localization task (Zhao, Vogel and Awh 2023) to prevent the rehearsal of memory items in working memory. In this task, there was a black fixation dot (0.35° x 0.35°) at the center of the screen along with six randomly placed colored squares that were presented for 250 ms on a given memory screen. After a blank retention interval of 1000 ms, the probe display of 6 colored squares were shown in their original locations. Only this time, one of the squares had been changed its color. Participants were asked to indicate the color-changed square by clicking on it with the computer mouse within a strict duration of 2000 ms. Participants were instructed to click the mouse whenever they noticed the correct answer, however, probes stayed on screen for exactly 2000 ms regardless of their answer. Considering that participants might be careless due to time pressure when clicking on the squares, a square that is 25% larger than the area of the original square was accepted as the correct answer area, by also making sure that this area would not overlap with the answer area of another square. Following the 250 ms interval after the participant's response, the second trial of the task would begin. The change localization task consisted of 12 trials for each block.

2.2.1.3 Phase 3 - test

The test phase consisted of 2 consecutive memory tasks. First, sequential memory, and second, temporal order memory task. In the sequential memory task, the 5th or 6th objects of randomly selected main events were presented at the center of the screen. Participants were then asked to indicate the category of the object that appeared after this object in the study (encoding) phase. The 5th object of the main event constituted the within-event condition since the next object would be the 6th object of the same main event. On the other hand, the 6th object of the main event constituted the across-events condition, as the next object would belong to the first object of the boundary event.

Next, participants were given the temporal order memory task. In this task, two objects were shown on the screen. One was either the 2nd or the 5th object of a randomly selected main event. The other was selected as 4 objects apart from the first object in the study phase. For example, in the within-event condition, the 2nd object of a main event was accompanied by the 6th object of the same main event at the test. However, in the across-events condition, the 5th object of a main event was presented with the 1st object of the following main event due to containing a boundary event of 2 items. Participants were then asked to specify which of the objects were displayed earlier in the study phase.

Both memory tasks included 4 probes divided equally per condition, 8 probes in total. Participants responded using the right and left arrow keys. In the sequential memory task, the left arrow indicated the animate category and the right arrow indicated the inanimate category. In the temporal order memory task, the left arrow was used for the objects on the left side of the screen, and the right arrow was used for the objects on the right side of the screen.

2.2.2 Block Distribution

There was 44 blocks in the experiment. Overall, each block consisted of a study phase, a filler task and a test phase containing 8 probes. Participants were allowed to take a self-paced break in between blocks. They were also informed about their behavioral task performances of the previous block during these breaks.

2.2.3 EEG Recordings

The EEG was recorded from 32 sintered - AG/AgCI electrodes positioned at International 10/20 System sites. The electrodes were attached to an elastic cap (actiCAP, Brain

Products). The EEG signal was amplified using Brain Products actiCHamp amplifier (actiCHamp Plus, Brain Products GmbH, Gilching, Germany) and was digitized at a 1000 Hz sampling rate.

The vertical EOG (VEOG) was recorded from two external electrodes that were located approximately 2 cm above and below the right eye. Two electrodes (F7 and F8) located approximately 1 cm lateral to the external canthi were used as HEOGs to detect horizontal eye movements. Two electrodes (TP9 and TP10) attached to the two mastoids were used as reference electrodes whereas the left mastoid (TP9) was the online reference. Since the amplification of EEG channels and external EOG channels differs, we applied a scaling factor of 0.1 μV (Brain Vision Recorder | User Manual, 2018) to VEOGs to make the magnitude of the VEOG and HEOG recordings compatible with other EEG channels for both on-line visualization and off-line analysis. The EEG data was collected from the following electrodes with a customary layout optimized for collecting data mainly from the parietal and occipital regions: Fp1, Fp2, F3, F4, Fz, FC5, FC6, FC1, FC2, C3, C4, Cz, CP5, CP6, CP1, CP2, P7, P8, P3, P4, Pz, PO7, PO8, PO3, PO4, O1, O2, and Oz. We kept the impedance for the electrodes below 20 kΩ.

We carried out the EEG analyses using MATLAB R2022b (Mathworks, Natick, MA), the EEGLAB toolbox (version 2021.1; Delorme and Makeig 2004), the ERPLAB toolbox (version 8.30; Lopez-Calderon and Luck 2014), and custom scripts. Recording artifacts (muscle noise, slow drifts, saturation, and blocking) and ocular artifacts (eye movements and blinks) were detected manually by visual inspection. Rejection of the artifacts was performed only before hypothesis testing. Trials containing such artifacts were excluded from the analysis. After artifact rejection, we excluded datasets with less than 80 trials from the analysis.

The data was filtered by an IIR Butterworth filter with a band-pass of 0.01-40 Hz using the pop_basicfilter.m function of ERPLAB. The data was then re-referenced offline to the average of the right (TP10) and left (TP9) mastoids. The noisy channels were interpolated using the pop_interp.m function of EEGLAB. Each event was counted as a separate epoch; for main events, one epoch would consist of 6 consecutive stimuli, and for boundary events, one epoch would consist of 2 consecutive stimuli. Considering the length of these epochs, a baseline period of 500 ms prior to the stimulus onset was included in the ERP analyses. All types of epoching were done using the pop_epoch.m function of EEGLAB.

2.2.3.1 ERP analysis: CDA

The CDA was measured at P7/8, PO7/8, and O1/2 as the mean voltage difference at electrodes contralateral versus ipsilateral to the location of each target object between 400 ms to 1000 ms after the onset of this target object (Günseli et al. 2019; Ikkai, McCollough and Vogel 2010; Vogel et al. 2005; Vogel and Machizawa 2004). We first compared the CDA amplitude of both main and boundary event items against 0 to determine if we observe CDA. We then tested our hypotheses using different approaches. We looked for a linear trend in the CDA amplitude between the second and sixth items of an event for the accumulation account. A linear trend in the CDA amplitude in 5 consecutive items would account for the accumulation of instances until WM capacity is reached within an event. We chose only 4 items for this test given the limited capacity of visual WM which is about 3-4 items (Awh, Barton and Vogel 2007; Luck and Vogel 1997).

2.2.3.2 Time-frequency analysis

We then conducted a time-frequency analysis to explore the involvement of attentional processes in memory reactivation (Fukuda and Woodman 2017; Günseli et al. 2019). To test our hypotheses regarding the reactivation account of memoranda, we compared the alpha-band power of the first items of main and boundary events with a paired samples t-test. Using the same test, we also compared the average bilateral alpha power of the first 4 items of the main event with the average of the first boundary item. To be able to do this, we analyzed bilateral alpha-band suppression between the time course of 400-1000 ms after each target onset, which was also the time window of the CDA analysis. Similarly, the same channels in the CDA analysis (P7/8, PO7/8, and O1/2) were used in the calculation. To see if the observed effects were specific to the alpha band, we conducted an analysis on the power of frequencies between 4 and 50 Hz. We then calculated the alpha-band suppression using a defined frequency between 8-12 Hz (Günseli et al. 2019) on a logarithmic scale.

We created a sinusoid (ei2ft) for each frequency, then converted it to Morlet wavelets by tapering it with a Gaussian ($e^{-\frac{t^2}{2s^2}}$; where t is time and s is the Gaussian width). The beginning and the end of the data were then padded with zero. All epoched data was restructured into one continuous EEG data, and then Fast Fourier Transform (FFT) was applied to both EEG and Morlet waves. For each frequency, we calculated the dot product of the Fourier-transformed EEG data and Morlet wavelet, then applied inverse FFT to each dot product. This procedure allowed us to be sure that the EEG data was convoluted for each Morlet wavelet. Lastly, we performed baseline normalization by calculating the average power activity between 500-200 ms before the target onset of all trials.

2.3 Results

The assumption of normality was met for most of the data in the following analyses. However, a departure from normality was observed for the sequential memory accuracy analysis, and we addressed this in the subsequent section.

2.3.1 Behavioral Results

2.3.1.1 Sequential memory

Accuracy

Using the Shapiro-Wilk test, we tested the assumption of normality and observed significant departure from normality (p < .05). Therefore a Wilcoxon signed-ranks test was conducted to compare the difference in sequential memory accuracy between within-event and across-event conditions (see Figure 2A). The test yielded that within-event accuracy was higher (M = 0.818, SD = 0.108) than across-event accuracy. (M = 0.527, SD = 0.227). The difference, 0.29 (95% CI [0.19 0.39], was significant (Z = 1.00, r = -0.99, p <.001).

Reaction time

According to the paired samples t-test results (see Figure 2C), the reaction time difference, -0.07 95% CI [-0.004 0.150] between the within (M = 2.07, SD = 0.877) and across (M = 2.00, SD = 0.899) event conditions was not significant, $t(22)$ = -1.95, p = 0.06, d = 0.40.

2.3.1.2 Temporal order memory

Accuracy

According to the paired samples t-test (see Figure 2B), the temporal order memory accuracy difference, 0.001, 95% CI [-0.035 0.036] was not significant between within and across events conditions, $t(22)$ = -0.02, p = 0.977, d = 0.006.

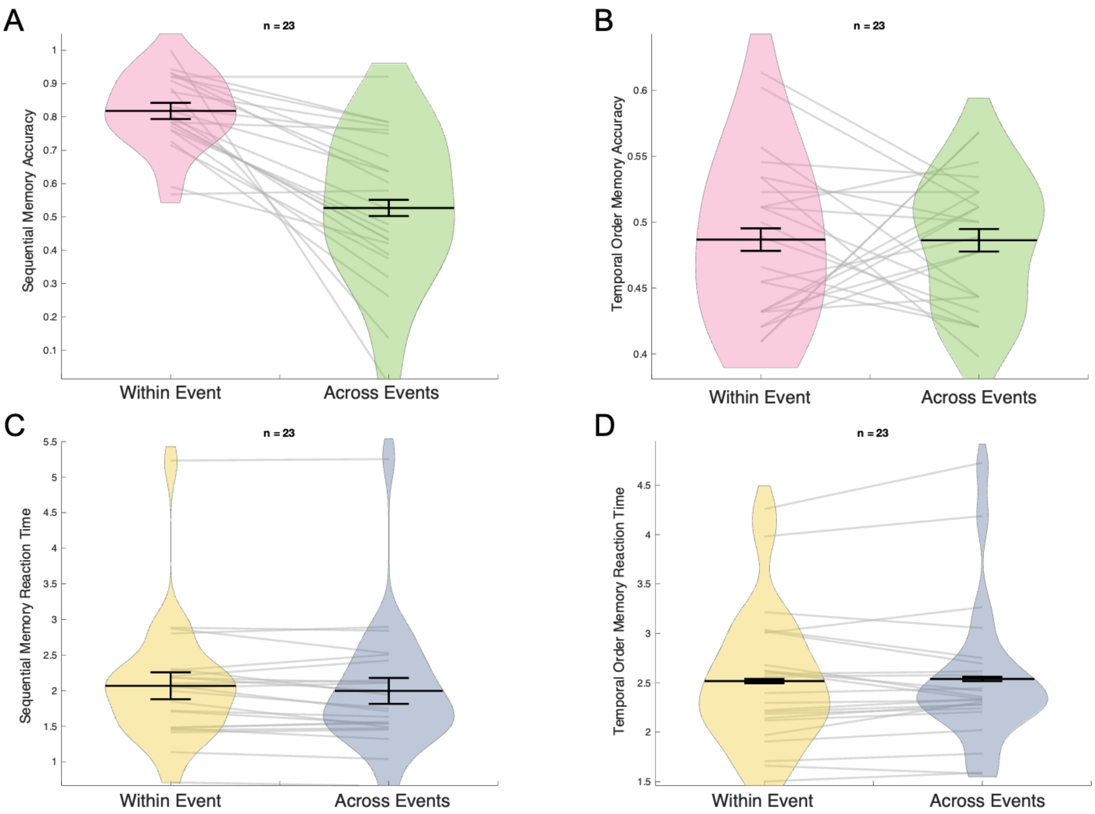
Reaction time

A paired samples t-test yielded that the difference (see Figure 2D), -0.02 95% CI [-0.11

0.06] in the reaction times between the within and across events conditions was not significant, $t(22) = 0.48$, $p = 0.632$, $d = -0.10$.

For each participant, an event segmentation score is calculated in both tasks and then used in the later correlational analyses. This score was obtained by subtracting across-event accuracy from within-event accuracy.

Figure 2.2 Behavioral analysis results



Accuracy violin plots of within and across-event conditions on (A) sequential memory task and (B) temporal order memory task. Reaction time violin plots of within and across-event conditions on (C) sequential memory task and (D) temporal order memory task. Error bars are 95% confidence intervals.

2.3.1.3 Change localization task

The average accuracy for the change localization task was 0.577 (*SD* = 0.135) which was similar to the mean accuracy (*M* = 0.586) of other change localization studies (Zhao et al. 2023).

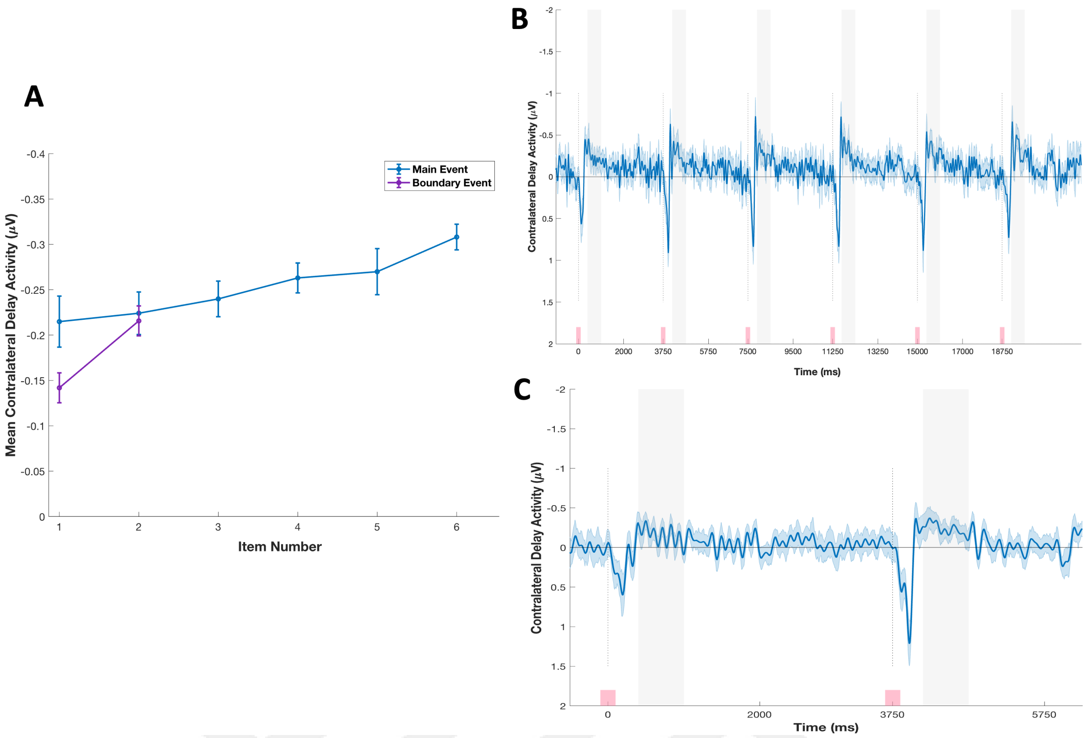
We extracted a working memory capacity estimate (K) score for each participant using a formula that was developed by Zhao et al. (2023) and was as follows: K = Acc(change localization) * N^2 - N / N - 1, where Acc(change localization) was the change localization task accuracy rate, and N was the set size, which was 6 for each participant. A higher K score would represent a higher working memory capacity. We obtained an average K score of 1.46 (*SD* = 0.807, 95% CI = [1.13 1.79]) which was considerably low compared to the average K scores (*M* = 2.66, *SD* = 0.83) of relevant change detection studies (Balaban, Fukuda and Luria 2019). Considering that the change localization task appeared after each block which participants had to restrict both eye and body movements, we believe that the K score we obtained may have been low due to the fatigue that they may have felt during blocks.

2.3.2 EEG Results

2.3.2.1 Accumulation account

The repeated measures ANOVA did not yield a significant difference in the CDA between the time points of the second and sixth items, $F(4, 88) = 2.172$, $p = 0.07$, $\eta^2 = 0.09$. Contrast analysis, on the other hand, revealed a significant linear trend in CDA between the course of the second and sixth items, $t(88) = -2.87$, $p < .01$ (see Figure 3A). We also tested if the CDA increased during boundary events, and found a significant increase $t(22) = 2.23$, $p < .05$, $d = 0.46$, between the first (*M* = -0.14, *SD* = 0.28) and second items (*M* = -0.21, *SD* = 0.34).

Figure 2.3 The CDA results

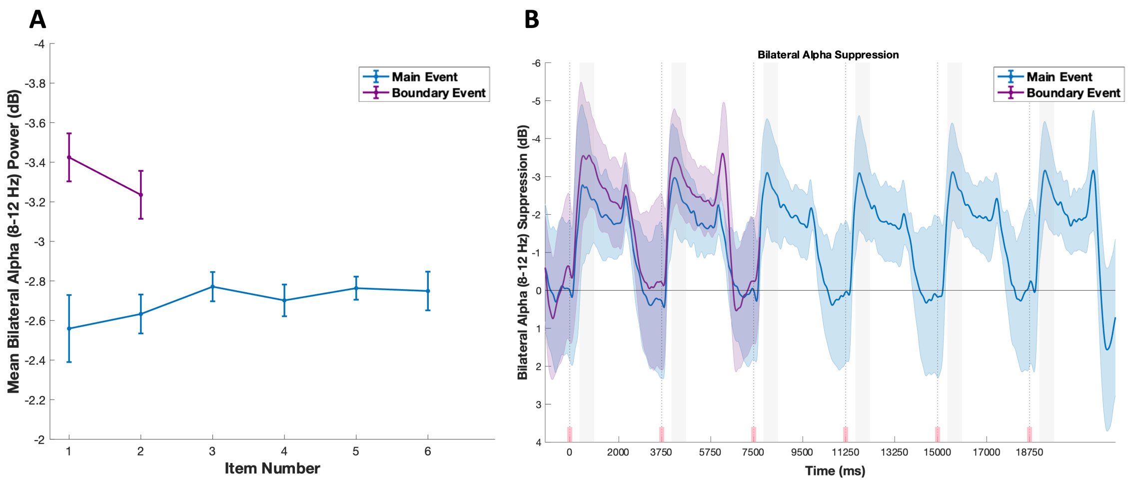


(A) The mean CDA amplitude of each item in main vs boundary events, depicted in a line plot. Main events are shown in blue, boundary events are shown in red. (B) The CDA amplitude over time in main events. Pink bars represent the stimulus onsets respectively. The CDA time frames we used in our analyses are depicted in light grey. (C) The CDA amplitude over time in boundary events. Error bars are 95% confidence intervals.

2.3.2.2 Reactivation account

A paired samples t-test was conducted to see if the bilateral alpha suppression during the first item of the main event was significantly different from the suppression during the first boundary item (see Figure 4A). The test confirmed our hypothesis by revealing that the bilateral alpha suppression was significantly higher, $t(22) = 4.22$, $p < .001$, $d = 0.88$, during the first boundary event item ($M = -3.42$, $SD = 2.40$) compared to the first item of the main event ($M = -2.56$, $SD = 1.81$). We carried out another paired samples t-test to see if the average alpha suppression between the first four items in main events significantly differed from the average bilateral alpha suppression of the first boundary item. Revealing another significant result, $t(22) = 2.79$ $p < .05$, $d = 0.58$, this analysis similarly showed that the first item of the boundary events had higher ($M = -3.42$, $SD = 2.40$) bilateral alpha suppression compared to the average of the first four items of the main events ($M = -2.67$, $SD = 2.09$). We finally tested whether there was a significant drop in mean bilateral alpha suppression between the first and second items of the boundary events. There was no significant drop between the first (M = -3.42, SD = 2.40) and second (M = -3.24, SD = 2.68) boundary items, $t(22)$=-0.78, p = .44, d = -0.16, which we interpreted this result as a continuum of the alpha suppression during the second items of boundary events.

Figure 2.4 The bilateral alpha suppression results

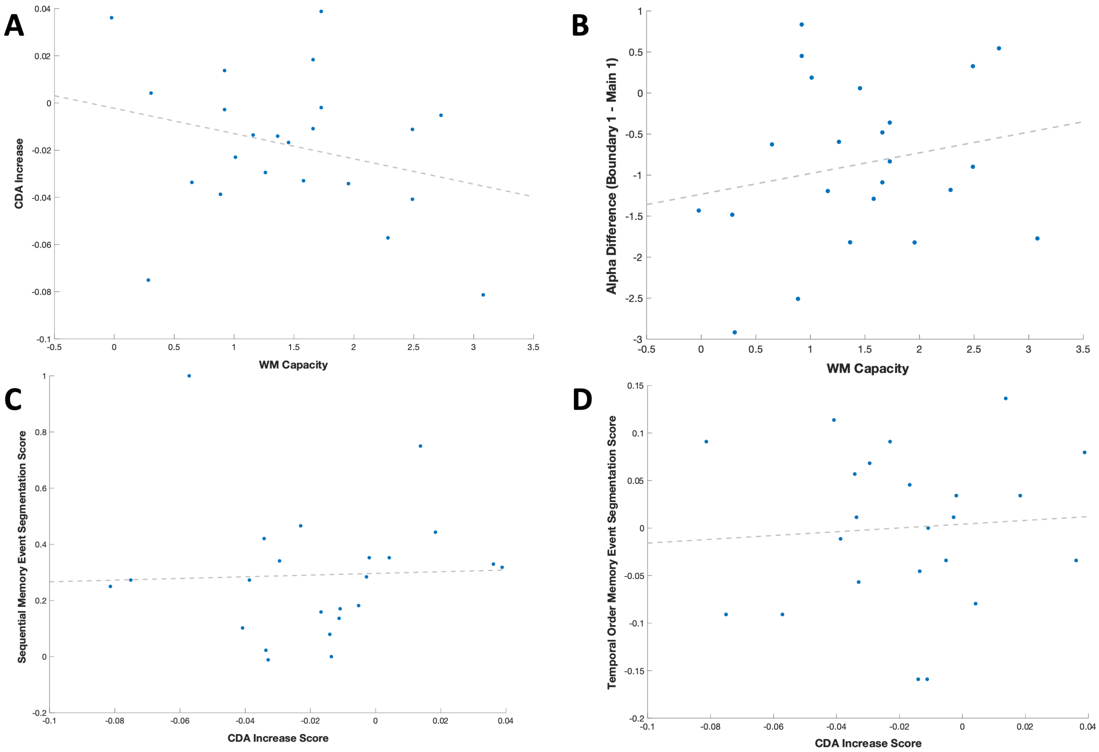


(A) The bilateral alpha suppression across main and boundary event items, depicted in a line graph. (B) The bilateral alpha suppression during both main and boundary events over time. Pink bars represent the stimulus onsets respectively. The time frames for the bilateral alpha calculation used in our analyses are depicted in light grey.

2.3.2.3 Correlational analyses

We also conducted correlational analyses (see Figure 5) to validate the CDA analysis, mainly to investigate the relationship between CDA increase per participant and their WM capacity score (K) that was obtained from the Change Localization Task. We expected people who had a higher CDA increase score over the main events would also have higher WM capacity. We also tested the accumulation account by comparing the CDA increase scores with participants' event segmentation scores that were obtained from the sequential memory and temporal order memory tasks. According to the accumulation account, if they successfully accumulated the items, they would have higher event segmentation scores from the behavioral tasks. However, the CDA increase was not significantly correlated with the WM capacity of participants (r = -0.28, p = 0.18) and segmentation scores of neither sequential memory (r = 0.03, p = 0.85), nor temporal order memory (r = 0.07, p = 0.73). Another correlational analysis was performed to determine if the bilateral alpha suppression difference between the first items of boundary and main events was significantly correlated with WM capacity. People with higher WM capacity seem to have an overall higher suppression difference (reactivation score), but unfortunately this correlation was not significant as well ($r = 0.20$, $p = 0.34$).

Figure 2.5 The results of the exploratory correlation analyses



The scatter plots depicting the correlation between (A) the CDA increase per participant and WM capacity, (B) the bilateral alpha power difference of first items and WM capacity, (C) sequential memory event segmentation score and the CDA increase per participant, and (D) temporal order memory event segmentation score and the CDA increase per participant.

2.4 Discussion

In our study, we attempted to explore and reconcile the two prominent accounts on how WM is involved in event segmentation. In our exploration, we first had to behaviorally assess event segmentation in order to make sure it occurs, thus we used two behavioral tasks: Sequential and Temporal Order Memory. We claimed that the average accuracy and reaction time would be significantly and respectively higher and faster within events, for both tasks. We found no such difference between within and across event conditions in the temporal order memory task. Although it is frequently shown in the literature that the within-event temporal order memory was significantly better, there is also a growing number of counter-evidence in recent studies (Wen and Egner 2022). In addition to their experimental findings where the presence of context during the test also affected their finding, they claim that in our everyday lives, we tend to remember the order of events better than the order of memoranda within an event. In our case, the extended duration of stimuli and ITIs would be a possible reason for fatigue, therefore causing participants to lose the ability to successfully track and encode the time and order of the items, resulting in an insignificance between conditions.

However, sequential memory results revealed that participants were indeed better at remembering the category of the next item when both belonged to the same event, with no significant difference in reaction times. Having this result, we can claim that we successfully observed event segmentation. We expected to monitor a gradual CDA increase between the second and last items during main events to be able to successfully support the accumulation account. For the reactivation account, we predicted a significant difference between bilateral alpha suppressions of main and boundary events, specifically a higher suppression during the first boundary event item compared to the first main event item. Both findings were consistent with our hypotheses. Despite the insignificance of the repeated measures ANOVA, there is a subtle but systematic CDA increase in main events. Even though this systematic increase is in line with the accumulation account, we believe that it is not sufficient to conclude that all items within an event are stored in WM since we don't know whether WM load increase, represented by CDA, includes all of the previously encountered items or a subset of them. Similarly, the low WM capacity score (K) we obtained also sheds light on the possibility that the linear increase trend of CDA may not represent the successfully encoded items in WM, but may rather reflect other cognitive demands.

We believe our results demonstrate greater evidence in support of the reactivation account. If WM activation were the same across main and boundary events, we would innately expect a 1-item increase in the suppression, thus an approximately equal value between the first items of the main and boundary events. However, we found the first item of the boundary events contained higher bilateral alpha suppression compared to both the first and the average of the first four items in the main events. Therefore, this activity does not only reflect the passive storage of one item in WM but also reactivates the previous event since the increase in alpha suppression shows greater effort to attend and maintain WM representations (Gunseli et al. 2018; Gunseli et al. 2019; Riddle et al. 2020). Unlike CDA, alpha suppression is inherently more sensitive, and it represents the attention to stimuli regardless of their presence on the screen. Given this sensitivity, it can be argued that if the accumulation account was analyzed by alpha power, it would also yield more significant results in both the omnibus and the linear contrast. However, we tested and eliminated this possibility, since the same analysis we used for the accumulation account did not reveal a significant result in either repeated measures ANOVA($F(4,88) = 0.458$, $p = 0.766$), nor the linear contrast ($t(88)=-0.838$, $p = 0.404$), meaning that bilateral alpha suppression did not have a significant increasing or decreasing trend in the main events.

3. GENERAL DISCUSSION

Our findings not only contribute to the event segmentation literature by supporting existing findings that claim that within-event items are encoded and recalled better than across-events items with the successful use of a relatively new Sequential Memory Task but also provide new insights into the role of WM in this intricate process. According to the results of this study, main events elicit a systematic CDA increase throughout approximately 6 items, but at the same, the beginning of boundary events are exposed to higher bilateral alpha suppression, which is an indicator of reactivation of previous memoranda. The co-existence of both the linear trend in CDA, and the higher bilateral alpha suppression in the beginning of boundary events indicates that the aforementioned claims of WM are not mutually exclusive, rather their concurrent presence can be an indicator of the dynamic nature of the relationship between WM and event segmentation.

Reflecting on the prominent accounts that explore the underlying mechanism of segmentation, our study offers additional evidence that contextual stability account plays an important role in event segmentation. We believe that our experiment does not reflect the prediction error, since all blocks have a consistent order, where every 6 main-event item is preceded with a categorically different 2-item boundary event 3 times in a single block, and for 44 blocks overall. The category change occurred in regular intervals and was expected. We therefore observed that the use of both categorical and auditorial changes strengthened the event segmentation as seen in the sequential memory test results.

While our study sheds light on the event segmentation literature, we also acknowledge its possible limitations. One might be the overall duration of the study. Participants were required to limit their eye and body movements such as blinking in the encoding phase of each block, especially when the same-event items were presented, because these movements caused distortions in the EEG data. They had a short rest period in between events, and in the filler task and test phases, but since the experiment lasted approximately 3 hours, it was a tiring process nevertheless. We also used CDA, which required them to fixate on the location cue in the middle of the screen. Combined with the restrictions in their eye and body movements, having to fixate on a cue, the possible discomfort caused by the electrodes on their faces, and the duration of the experiment, participants may have experienced fatigue and therefore lost the attention to successfully encode target items. The average K score (M=1.46) we obtained may also reflect the same argument, considering that it is considerably low compared to other change localization and detection studies, which can be seen as an indicator of participant fatigue.

Future EEG studies of event segmentation may benefit from shorter durations of encoding or item lists. They may also implement more frequent breaks between blocks to eliminate the effects of participant fatigue on both behavioral and neural measures. Overall, the role of WM in segmentation seems to be dynamic and needs further exploration with different methodologies to truly unravel its nature.

BIBLIOGRAPHY

Adam, Kirsten C. S., Matthew K. Robison, and Edward K. Vogel. 2018. "Contralateral Delay Activity Tracks Fluctuations in Working Memory Performance." *Journal of Cognitive Neuroscience* 30(September): 1229–1240.

Awh, Edward, Brian Barton, and Edward K. Vogel. 2007. "Visual working memory represents a fixed number of items regardless of complexity." *Psychological Science* 18(July): 622–628.

Baddeley, Alan. 2003. "Working memory: looking back and looking forward." *Nature Reviews. Neuroscience* 4(October): 829–839.

Balaban, Halely, Keisuke Fukuda, and Roy Luria. 2019. "What can half a million change detection trials tell us about visual working memory?" *Cognition* 191(October): 103984.

Becke, Andreas, Notger Müller, Anne Vellage, Mircea Ariel Schoenfeld, and Jens-Max Hopf. 2015. "Neural sources of visual working memory maintenance in human parietal and ventral extrastriate visual cortex." *NeuroImage* 110(April): 78–86.

beim Graben, Peter, and Jürgen Kurths. 2008. "Simulating global properties of electroencephalograms with minimal random neural networks." *Neurocomputing* 71(January): 999–1007.

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(May): 1106–1128.

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

Delorme, Arnaud, and Scott Makeig. 2004. "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis." *Journal of Neuroscience Methods* 134(March): 9–21.

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: The Official Journal of the Society for Neuroscience* 34(October): 13998–14005.

DuBrow, Sarah, and Lila Davachi. 2016. "Temporal binding within and across events." *Neurobiology of Learning and Memory* 134 Pt A(October): 107–114.

Ezzyat, Youssef, and Lila Davachi. 2011. "What constitutes an episode in episodic memory?" *Psychological Science* 22(February): 243–252.

Fukuda, Keisuke, and Geoffrey F. Woodman. 2017. "Visual working memory buffers information retrieved from visual long-term memory." *PNAS Proceedings of the National Academy of Sciences of the United States of America* 114(20): 5306–5311.

Goldman-Rakic, Patricia S. 2011. "Circuitry of Primate Prefrontal Cortex and Regulation of Behavior by Representational Memory." In *Comprehensive Physiology*. John Wiley & Sons, Ltd pp. 373–417.

Gunseli, E., J. Fahrenfort, D. van Moorselaar, K. Daoultzis, M. Meeter, and C. N. L. Olivers. 2018. "Unattended but actively stored: EEG dynamics reveal a dissociation between selective attention and storage in working memory.".

Gunseli, Eren, Christian Olivers, and Martijn Meeter. 2014. "Effects of Search Difficulty on the Selection, Maintenance, and Learning of Attentional Templates." *Journal of cognitive neuroscience* 26(March).

Gunseli, Eren, Martijn Meeter, and Christian N.L. Olivers. 2014. "Is a search template an ordinary working memory? Comparing electrophysiological markers of working memory maintenance for visual search and recognition." *Neuropsychologia* 60(July): 29–38.

Güler, Berna, Fatih Serin, and Eren Gunseli. 2023. "Prediction error is out of context: The dominance of contextual stability in segmenting episodic events." (December).

Günseli, Eren, Johannes Jacobus Fahrenfort, Dirk van Moorselaar, Konstantinos Christos Daoultzis, Martijn Meeter, and Christian N. L. Olivers. 2019. "EEG dynamics reveal a dissociation between storage and selective attention within working memory." *Scientific Reports* 9(September): 13499.

Hard, Bridgette Martin, Gabriel Recchia, and Barbara Tversky. 2011. "The shape of action." *Journal of Experimental Psychology. General* 140(November): 586–604.

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(July): 1075–1090.

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(September): 151–164.

Ikkai, Akiko, Andrew W. McCollough, and Edward K. Vogel. 2010. "Contralateral Delay Activity Provides a Neural Measure of the Number of Representations in Visual Working Memory." *Journal of Neurophysiology* 103(April): 1963–1968.

Kaufman, L., B. Schwartz, C. Salustri, and S. J. Williamson. 1990. "Modulation of Spontaneous Brain Activity during Mental Imagery." *Journal of Cognitive Neuroscience* 2(April): 124–132.

Konkle, Talia, and Alfonso Caramazza. 2013. "Tripartite organization of the ventral stream by animacy and object size." *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 33(June): 10235–10242.

Konkle, Talia, and Aude Oliva. 2012. "A familiar-size Stroop effect: Real-world size is an automatic property of object representation." *Journal of Experimental Psychology: Human Perception and Performance* 38(3): 561–569.

Konkle, Talia, Timothy F. Brady, George A. Alvarez, and Aude Oliva. 2010. "Conceptual Distinctiveness Supports Detailed Visual Long-Term Memory for Real-World Objects." *Journal of Experimental Psychology. General* 139(August): 558–578.

Kosie, Jessica E., and Dare Baldwin. 2019. "Attention rapidly reorganizes to naturally occurring structure in a novel activity sequence." *Cognition* 182(January): 31–44.

Kurby, Christopher A., and Jeffrey M. Zacks. 2008. "Segmentation in the perception and memory of events." *Trends in cognitive sciences* 12(February): 72–79.

Lopez-Calderon, Javier, and Steven J. Luck. 2014. "ERPLAB: an open-source toolbox for the analysis of event-related potentials." *Frontiers in Human Neuroscience* 8: 213.

Luck, Steven J., and Edward K. Vogel. 1997. "The capacity of visual working memory for features and conjunctions." *Nature* 390(November): 279–281.

Luria, Roy, Halely Balaban, Edward Awh, and Edward K. Vogel. 2016. "The contralateral delay activity as a neural measure of visual working memory." *Neuroscience and biobehavioral reviews* 62(March): 100–108.

Miller, E. K., and J. D. Cohen. 2001. "An integrative theory of prefrontal cortex function." *Annual Review of Neuroscience* 24: 167–202.

Ongchoco, Joan Danielle K., and Brian J. Scholl. 2019. "Did that just happen? Event segmentation influences enumeration and working memory for simple overlapping visual events." *Cognition* 187(June): 188–197.

Radvansky, Gabriel A., and David E. Copeland. 2006. "Walking through doorways causes forgetting: situation models and experienced space." *Memory & Cognition* 34(July): 1150–1156.

Radvansky, Gabriel A., Sabine A. Krawietz, and Andrea K. Tamplin. 2011. "Walking through doorways causes forgetting: Further explorations." *Quarterly Journal of Experimental Psychology (2006)* 64(August): 1632–1645.

Riddle, Justin, Jason M. Scimeca, Dillan Cellier, Sofia Dhanani, and Mark D'Esposito. 2020. "Causal Evidence for a Role of Theta and Alpha Oscillations in the Control of Working Memory." *Current Biology* 30(May): 1748–1754.e4.

Sargent, Jesse Q., Jeffrey M. Zacks, David Z. Hambrick, Rose T. Zacks, Christopher A. Kurby, Heather R. Bailey, Michelle L. Eisenberg, and Taylor M. Beck. 2013. "Event segmentation ability uniquely predicts event memory." *Cognition* 129(November): 241–255.

Shin, Yeon Soon, and Sarah DuBrow. 2021. "Structuring Memory Through Inference-Based Event Segmentation." *Topics in Cognitive Science* 13(1): 106–127.

Silva, Marta, Christopher Baldassano, and Lluís Fuentemilla. 2019. "Rapid Memory Reactivation at Movie Event Boundaries Promotes Episodic Encoding." *The Journal of Neuroscience* 39(October): 8538–8548.

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: CB* 27(November): 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(May): 449–455.

Swallow, Khena, Jeffrey Zacks, and Richard Abrams. 2009. "Event Boundaries in Perception Affect Memory Encoding and Updating." *Journal of experimental psychology. General* 138(June): 236–57.

Tulving, Endel. 1993. "What Is Episodic Memory?" *Current Directions in Psychological Science* 2(June): 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. 2022. "Time changes: Timing contexts support event segmentation in associative memory." *Psychonomic Bulletin & Review* 29(April): 568–580.

Vogel, Edward K., and Maro G. Machizawa. 2004. "Neural activity predicts individual differences in visual working memory capacity." *Nature* 428(April): 748–751.

Vogel, Edward K., Andrew W. McCollough, and Maro G. Machizawa. 2005. "Neural measures reveal individual differences in controlling access to working memory." *Nature* 438(November): 500–503.

Wang, Yuxi Candice, and Tobias Egner. 2022. "Switching task sets creates event boundaries in memory." *Cognition* 221(April): 104992.

Wen, Tanya, and Tobias Egner. 2022. "Retrieval context determines whether event boundaries impair or enhance temporal order memory." *Cognition* 225(August): 105145.

Williamson, S. J, L Kaufman, Z. L Lu, J. Z Wang, and D Karron. 1997. "Study of human occipital alpha rhythm: the alphon hypothesis and alpha suppression." *International Journal of Psychophysiology* 26(June): 63–76.

Zacks, Jeffrey M., and Khena M. Swallow. 2007. "EVENT SEGMENTATION." *Current directions in psychological science* 16(April): 80–84.

Zhao, Chong, Edward Vogel, and Edward Awh. 2023. "Change localization: A highly reliable and sensitive measure of capacity in visual working memory." *Attention, Perception & Psychophysics* 85(July): 1681–1694.