THE EFFECTS OF CONTEXT ON WORKING MEMORY AND RHYTHMS OF ATTENTION

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ABSTRACT

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In everyday life, context affects how we interpret task-related information while performing a given task. In this thesis, I investigated the effects of context on two fundamental cognitive stages of information processing, working memory (WM) and attention. In Experiment 1, we explored the effects of task-irrelevant context changes on memory reactivation. We found that task-irrelevant context changes reactivate task-relevant target information in WM. In Experiment 2, we investigated the effects of the reliability of cues that signal target locations on the properties of rhythmic sampling of attention. Our preliminary results showed that if the cue was reliable, the sampling frequency was lower for locations where the target wasn't expected. However, we observed that this trend reversed when we decreased the reliability of the cue. In the light of two studies' findings, I suggest that contextual features can affect working memory even if they are task-irrelevant, and task-relevant contextual changes can affect attention due to task demands. Our results demonstrate that contextual features should be more emphasized in working memory and attention studies.

ÖZET

BAĞLAMIN İŞLEYEN BELLEK VE DIKKAT RITIMLERINE ETKISI

ŞAHCAN ÖZDEMIR

PROGRAM ADI YÜKSEK LİSANS TEZİ, MAYIS 2023

Tez Danışmanı: Dr. Öğr. Üyesi Eren Günseli

Anahtar Kelimeler: Bağlam, Çalışan Bellek, Uzun Süreli Bellek, Dikkat, Ritmik Örnekleme

Günlük yaşamda bağlam, herhangi bir görevi yerine getirirken görevle ilgili bilgileri nasıl yorumladığımızı etkiler. Bu tezde, bağlamın bilgi işlemenin iki temeli olan çalışan bellek (ÇB) ve dikkat üzerindeki etkilerini araştırdım. İki çalışmada, bağlamı *görevle ilgili* ve *görevle ilgisiz* olarak kategorize ettim ve buna göre manipüle ettim. İlk çalışmada, görevle ilgisiz bağlamın bellek yeniden etkinleştirmeleri üzerindeki etkilerini araştırdım. Sonuçlar, görevle ilgili olmayan bağlamsal değişikliklerin hedef bilgileri ÇB'de yeniden etkinleştirdiğini gösterdi. İkinci çalışmada, teta aralığında bilgi örnekleyen dikkatin ritmik örnekleme mekanizmalarını uzamsal işarete ilişkin güvenirliğin etkileyip etkilemediğini araştırdım. İlk sonuçlarımız, ipucu güvenilirliği daha yüksek olduğunda, geçersiz konumlardan örnekleme sıklığının geçerliden daha düşük olduğu ve bunun tersinin daha düşük ipucu güvenilirliği için olduğu yönünde bir eğilim gösterdi. İki çalışmanın bulguları ışığında, bağlamsal özelliklerin görevle alakasız olsalar bile bilginin nasıl işlendiğini etkileyebileceğini ve görevle ilgili bağlamsal değişikliklerin görevin yapısı ve gereklilikleri nedeniyle ilgili mekanizmaları etkileyebileceğini öne sürdüm. Özet olarak, bağlamın görevle ilişkisinin etkileri araştırılarak, bellek ve dikkat çalışmalarında bağlamsal özellikler daha fazla vurgulanmalıdır.

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Dedication page
Dedicated to my little sister Reyhan

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CDA	Contralateral Delay Activity	5, 6, 12, 13, 14, 15, 16, 18, 19, 20
EEG	Electroencephalogram	vii, viii, 5, 7, 11, 13, 14, 18, 23, 33
FFT	Fast Fourier Transform	13, 27
LTM	Long-Term Memory	2, 4, 5, 6, 12, 14, 15, 18, 20, 21
PLV	Phase Locking Value	27, 30, 31
RT	Reaction Times	ix, 14, 18, 27, 28, 29
SOA	Sitmulus Onset Asynchrony	22, 23, 24, 25, 26, 27, 29
TF	Time-Frequency	30, 32, 33
WM	Working Memory	1, 2, 4, 5, 6, 12, 14, 15, 18, 19, 20, 21, 23, 35

1. GENERAL INTRODUCTION

Context affects how we interpret information. Consider a red light as the information. The same information means you need to stop when you encounter it in traffic, but it signals that your coffee is ready if it appears in your coffee machine. Contextual cues can also affect the structure of the tasks we perform. For example, the optimal settings of driving a car (e.g., the proper speed, things to watch out for like animals) would be different on a highway or a street in a small town. In this thesis, I aim to understand how context affects the underlying cognitive mechanisms of processing task-relevant information. To achieve this aim, in two studies, I explored the effects of context on working memory (WM) and attention, two fundamental cognitive stages of information processing. More specifically, in the first study, I focused on the effects of task-irrelevant contextual changes (i.e., background color) on the reactivation of task-relevant memories in WM (Chapter 2; Baddeley 2003, 2010; Carlisle et al. 2011; Cowan 2017). In the second study, I examined the effects of the reliability of a spatial cue, which is a more task-related contextual setting, on the rhythmic sampling of attention (Chapter 3; Fiebelkorn, Saalmann, and Kastner 2013; Landau and Fries 2012).

The operational definition of context varies in studies of memory and attention. The location of the presented stimulus (Cai et al. 2022, 2018), time of the event (Pu et al. 2022), background images (Deffler, Brown, and Marsh 2015), or associated responses like fear of an aversive stimulus can set the context of a task (Cohen et al. 2019). Various approaches make the definition of context vague. For memory studies, Stark et al. (2018) attempted to standardize it by suggesting three tenets for considering a feature in an experiment as a context. According to this view, context needs to be stable over time, needs to group information, and its effect needs to be observable through behavior. But here, I extended this view in two ways. Both our manipulations of context were in line with the Stark et al. definition in terms of consistency, and grouping effect. However, I extended this view by suggesting effects of contextual features can be also observable only at the neural level but not behavioral (Chapter 2). Also I categorized the context manipulation as task-irrelevant and task-relevant. This categorization can be considered when identifying contextual manipulations for the following reasons: the context that is task-irrelevant may also affect how the target information is processed due to its immanence, and therefore it may be important to examine it; the effects of task-relevant context may be regulated by the requirements of the task demands, and how the manipulation interacts with the experimental design becomes important to examine. In Chapter 4, I discussed these differences in detail.

I manipulated context within the scope of the extended perspective I suggested in this thesis in two ways. First, I explored task-irrelevant context effects on the reactivation of LTMs in WM. WM maintains task-related information (Baddeley 2003, 2010; Carlisle et al. 2011; Cowan 2017). With repetition, this information can be handed off to long-term memory (LTM; Anderson 1983; Carlisle et al. 2011; Logan 1988). After its transition, the handed-off information can be reactivated in WM if there is an instruction that promotes better performance (Reinhart, McClenahan, and Woodman 2016) or signals higher reward value (Reinhart and Woodman 2014). Moreover, recent work from our lab found that switching across different task rules triggers the reactivation of task-relevant items (Senturk et al. 2023). However, how task-relevant contextual changes affect the storage of task-relevant information remains unclear. I tested this in Experiment 1 by manipulating the background color that does not have a direct relationship with the task structure.

Second, I explored the effects of task-relevant contextual changes on sampling visual information. Attention samples visual information from the outside world rhythmically (Dugué, Roberts, and Carrasco 2016; Fiebelkorn and Kastner 2019; Landau and Fries 2012. When the perceptual sensitivity to a location is enhanced, sensitivity to other possible locations in the visual field is suppressed. The attentional mechanism controls unattended locations for possible events by changing the weights of perceptual sensitivity between attended and unattended locations rhythmically (for a review see Fiebelkorn and Kastner 2019; VanRullen 2016). These processes are related in the alpha (8-12 Hz) oscillations of the attention network (Busch, Dubois, and VanRullen 2009; Dugué, Marque, and VanRullen 2011; Fries 2023). Also, this mechanism can be observable overtly in rhythmic changes in behavioral performance (Chen et al. 2017; Landau and Fries 2012; Su et al. 2021). On the attended location, the behavioral performance of target detection oscillates in theta (4-8 Hz) frequency range (Chen et al. 2017; Landau and Fries 2012; Su et al. 2021; VanRullen 2016). To date, it is unclear if attentional rhythms are a reflection of biological constraints or if they are sensitive to task-demands to optimize the trade off between the encoding of novel information from the external world and internal processes related to the processing of recently and formerly acquired information. Importantly, only the latter would predict a change in the characteristics (e.g., phase, frequency) of these behavioral oscillations in a top-down manner. To that end, I manipulated the validity ratio (reliability) of spatial cues that signal target location, as it determines strategies regarding the allocation of attention over space.

2. EFFECTS OF CONTEXT ON MEMORY REACTIVATION

2.1 Introduction

Humans use particular information in particular task settings. For example, when driving, we represent information regarding pedals, mirrors, other vehicles, and traffic lights. When performing a task, WM maintains task-relevant information (Baddeley 2003, 2010; Carlisle et al. 2011; Cowan 2017). On the other hand, with repeated storage, LTM takes over the role of keeping task-relevant information (Anderson 1983; Carlisle et al. 2011; Logan 1988) . LTM has been shown to be strongly linked to the particular context in which items occur (Godden and Baddeley 1975; Robin, Wynn, and Moscovitch 2016; Tulving and Thomson 1973). However, the interplay between WM and LTM in storing task-relevant information during context changes remains unclear.

The effects of context on the encoding and retrieval of LTM are well established. For example, retrieval is more successful when it shares the same context with encoding (Godden and Baddeley 1975; Tulving and Thomson 1973). Moreover, being provided with any context (e.g., location) results in improved recall compared to not receiving a particular context even if the provided context is different from the encoding context (Robin, Wynn, and Moscovitch 2016). These results highlight the importance of forming item-context bindings for remembering items. The effects of changes in context have also been shown to determine the structure of episodic memories. We experience the world continuously but perceive and store events as segmented into meaningful parts (Zacks and Swallow 2007). Changes in contextual features such as background color, sound, and location result in the segmentation of events formed in episodic memory (Heusser et al. 2018; Horner et al. 2016; Raccah et al. 2022). These findings suggest that contextual changes affect how an item is preserved in LTM.

Even though the effects of context on the encoding and retrieval of LTMs are well established, how those changes affect WM is less clear. In daily life, there is an intimate relationship between the context and task-relevant information (e.g., while a red light can signal the need to stop on the road, it can indicate that your coffee machine is preparing you a nice cup of coffee in the kitchen). Thus, we hypothesize that a close relationship with context should also exist for WM. One way to study this relationship would be to test the effects of contextual changes on WM reactivation. The storage of task-relevant information hands off from WM to LTM with repeated exposure (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Reinhart, McClenahan, and Woodman 2016). Given that the context affects how we interpret information and there are well-studied effects of context on LTM (Godden and Baddeley 1975; Heusser et al. 2018; Horner et al. 2016; Raccah et al. 2022; Robin, Wynn, and Moscovitch 2016; Tulving and Thomson 1973) , we hypothesize that, if the storage of task-relevant information in WM is dependent on the context, then a change in context should result in the reactivation of information handed off to LTM back in WM. Recent work from our lab found that changes in task rules triggers such reactivation (Senturk et al. 2023). Observing memory reactivation for background color changes would suggest that task-irrelevant contextual changes promote memory reactivation in a similar way as task-related changes. On the other hand, if WM operates independent of the context, then information handed off to LTM should remain in LTM without being reactivated in WM. This would suggest that reactivation of task-relevant items might be triggered solely by changes in task-relevant aspects.

The present study therefore assesses the effect of context changes on the relative involvement of WM and LTM in storing task-relevant information. To achieve this, participants performed a WM task in which the target object repeats across trials. The repetition of the target object is expected to result in its handoff from WM to LTM (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Reinhart, McClenahan, and Woodman 2016). During this repetition, the context, which is the background color, occasionally changed. The context was completely task-irrelevant, as it didn't predict the correct response. We used contralateral delay activity (CDA), a widely used EEG index of WM storage (Luria et al. 2016; Vogel, McCollough, and Machizawa 2005) to assess the involvement of WM in storing information available in LTM. Previous research showed that CDA scales with the number of items kept in WM and reaches an asymptote at individuals' WM capacity (Luria et al. 2016; Vogel and Machizawa 2004; Vogel, McCollough, and Machizawa 2005). Moreover, it has been shown to reflect the number of items in WM and not their complexity (Ikkai, McCollough, and Vogel 2010). Furthermore, CDA decreases when the same item is repeatedly stored in WM, reflecting the handoff of the item's representation from WM to LTM (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Gunseli, Meeter, and Olivers 2014; Reinhart, McClenahan, and Woodman 2016). Thus, it is a suitable tool to measure WM involvement in storing items. Here, we anticipate that the CDA will decrease with the repetitions of the same item across trials as previously shown (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Gunseli, Meeter, and Olivers 2014; Reinhart, McClenahan, and Woodman 2016). To test our main hypothesis, we evaluated the CDA for such repeated items when the context changes. Our results showed that the CDA decreased with repetition as a sign of transition to LTM and recovered when context changes despite the same target being repeated. This outcome suggests that task-irrelevant contextual changes trigger an automatic reactivation of task-relevant items that have been transferred to LTM. By doing so, it informs our understanding of how previously learned information is represented in memory for novel contexts.

2.2 Methods

2.2.1 Participants

29 students from Sabancı University participated for course credits in this study, 7 participants were excluded from further analysis due to exclusion criteria (explained below). The analyses were conducted with 22 participants (Mean_{age} = 21.7, SD = 2.9), 6 males and 16 females. We determined the target participant number based on our previous work that used a similar experimental design (Senturk et al. 2023). Effect sizes from four studies that used CDA as a memory load measure were averaged (Berggren and Eimer 2016; Gunseli, Olivers, and Meeter 2014; Reinhart, McClenahan, and Woodman 2016; Xie and Zhang 2018). Following Schönbrodt and Wagenmakers (2018), Dienes (2021) guidelines and the associated R package by Schönbrodt & Stefan (2019) (github.com/nicebread/BFDA), a sequential design approach was conducted. Cauchy distribution as an uninformed and objective distribution was chosen as prior with half of the estimated effect size as the scaling parameter (Dienes 2021). We calculated the minimum number of participants as 20 by estimating the number of participants needed for a power of .90, and a false positive rate of .02 under the estimated effect size d=1.12. The number of participants as a stopping rule was estimated as 70 with the smallest effect size in the abovementioned studies, which is d= 0.48. Bayes Factor was planned to be calculated first when the number of participants reaches 20 then aimed to be calculated after every 5 new participants. Data collection was decided to continue until the

Bayes Factor is between 1/6 and 6 or the number of participants reaches 70. We collected 22 participants in total after exclusion. Because we were late in checking statistical analyzes in 20 participants, we exceeded the specified number of 20 without calculating the Bayes Factor. We realized the mistake with 22 participants. We first calculated the BF for the first 20 participants and the result was above 6, then we calculated the BF again with all 22 participants and the results were still similar (above 6) so we stopped the data collection at 22 participants.

Since color served as context in this study, before the experiment, each participant took an online Ishihara Color Blindness test, which is suggested to be as efficient as traditional paper tests (Marey, Semary, and Mandour 2015). Participants viewed plates, which consist of solid circles of various colors and sizes that form a number or a pattern. They indicated the number written on the plate or counted the number of lines on the pattern. If they respond correctly to less than 13 plates out of 38, they are excluded from the experiment due to red-green color vision deficiency (Marey, Semary, and Mandour 2015).

After the EEG data artifact rejection process (see below), participants who have less than 60 non-rejected trials per condition or with accuracies lower than 80% were excluded from further analysis. New participants were recruited to replace excluded participants. This study was approved by the Sabancı University Ethical Committee. All participants signed a consent form to participate in the study.

2.2.2 Ethics Statement

This study was performed in line with the principles of the Declaration of Helsinki. The ethics approval was granted from the Sabancı University Research Ethics Committee.

2.2.3 Stimuli

Images that were used in the current study (Senturk et al. 2023) brought together with additionally collected images to create a set of 2880 images of real-world objects (Konkle and Caramazza 2013; Konkle and Oliva 2012; Konkle et al. 2010;Google Images) in total. Images were resized to contain approximately the same number of non-transparent pixels. Half of the images were selected as target objects and the other half selected as non-target. Target objects were separated into two groups, animate and inanimate. Animate and inanimate groups contained 60 object categories, each category consisting of 12 pictures, thus making 1440 target objects in total. Each object (7.1° x 7.1°) was presented once as a target throughout the experiment. Each category became a target twice. Two objects from each object category were a target during the experiment.

Each trial was presented with a color as a context. Context color could be either red (HSL: 228, 44, 146) or green (H:71, S:67, L:145). Color was presented as a rectangular frame surrounding the target item of each trial (16.7° x 10°). The experiment had 1440 trials. Each target object repeated for 6 trials in a row. Through these repetition series, the context could change in the 1^{st} and/or 5^{th} repetition.

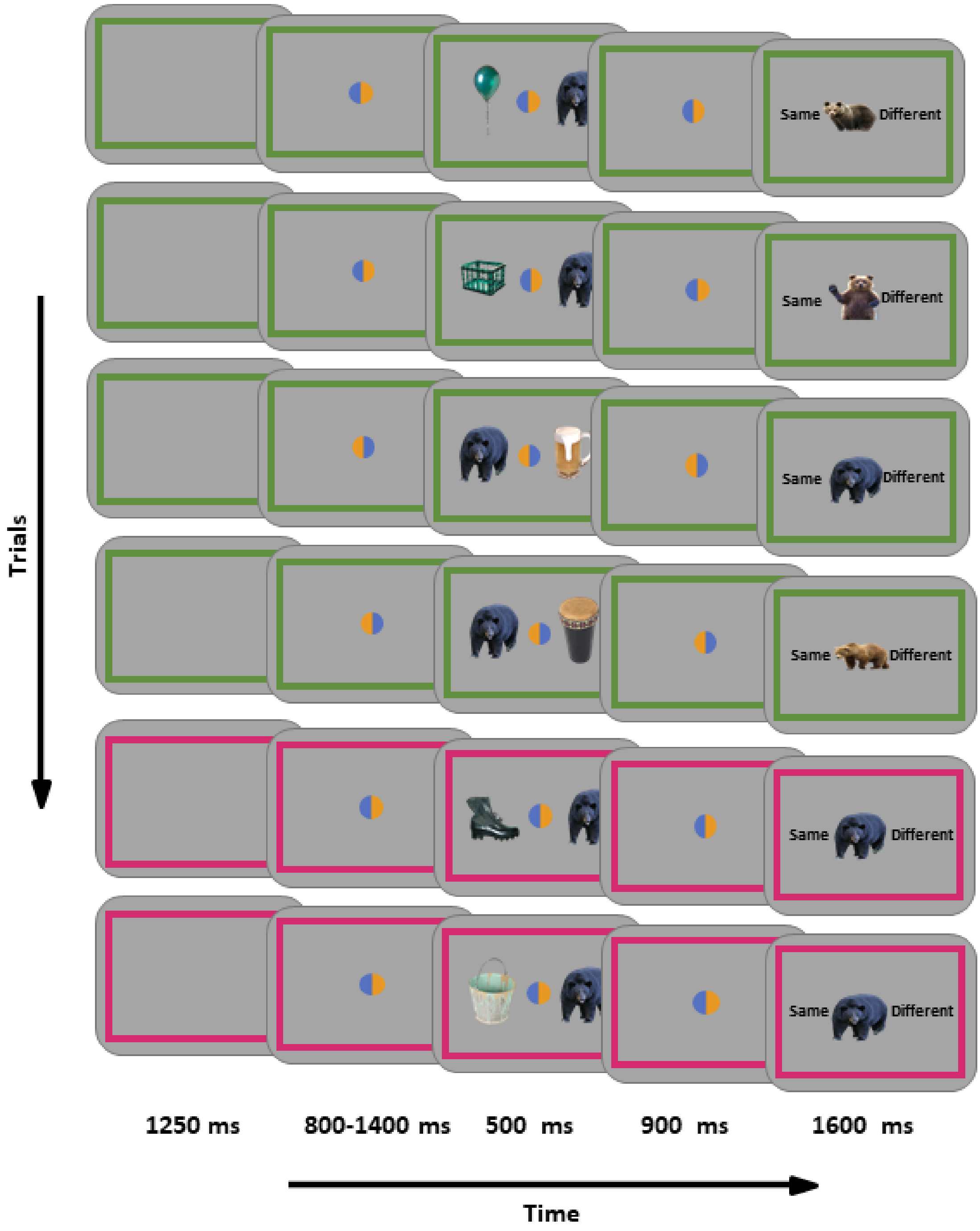
Participants viewed the experiment 85 cm away from the computer screen. The background color of the experiment was grey. The location cue was a vertically halved, bicolored circle (0.35° x 0.35°), with one side being navy blue (H:240, S:100, L:25) and the other side orange (H:38,5, S:100, L:50). For a given participant, a particular color indicated the side of the screen on which the target was presented, and it was counterbalanced across participants.

2.2.4 Design and Procedure

2.2.4.1 Trial design

The trial design is depicted in Figure 2.1. The task was to indicate if the probe item matches the target item. Each trial started with a presentation of the context color for 1250 ms. Then, the location cue appeared for a jittered duration of 800-1400 ms and remained on the screen until the probe was at the center of the screen. Following the location cue, two objects were presented. One of the objects was presented at the left and one to the right of the location cue, for 500 ms. Participants were instructed to memorize the target presented on the cued side. They were instructed to fixate on the location cue. Next, there was a retention interval of 900 ms during which the cue remained on the screen. After the retention interval, the probe was shown at the center of the screen. On each side of the probe, there were two response labels, “Same” and “Different” (0.7°). Participants pressed the left or right arrow key on a Turkish QWERTY computer keyboard to indicate their response (Figure 1; e.g., the left arrow to respond Same and the right arrow to respond Different). The locations of each response label were counterbalanced across participants. The probe remained on the screen until response or up to 1600 ms. Participants received visual feedback upon their response (‘correct’ or ‘incorrect’) or after 1600 ms (‘miss’). The feedback was shown at the center of the screen for 300 ms (5° x 5°). Lastly, a blank inter-trial interval was jittered between 300 and 700 ms. The context color frame was presented in the background (16.7° x 10°) throughout the trial except the inter-trial interval.

Figure 2.1 Illustration of the experimental procedure



Each trial will start with the presentation of context, i.e., the background color, which will be filled in the real experiment but shown here only as a frame for illustration purposes. Then, participants will see the location cue that indicates which object will be the target object. Following the location cue, target object will be shown in the indicated side and non-target object will be presented at contralateral side. After a brief retention interval, participants will be shown a probe object and will indicate if it is the same as the target.

2.2.4.2 Trial distribution & block design

On each trial, the probe and the target were from the same object category. For each condition, the target was equally likely to be on the left or right on the target display. The target type was equally likely to be animate or inanimate.

The experiment began with a practice session of 25 trials minimum. The objects used during practice weren't shown in the main experiment. The practice session was repeated until participants achieved at least 80% accuracy. The experimental session was divided into 38 to 42 blocks of approximately 40 trials. The block and trial numbers varied to ensure each block starts with a new context and a new target. At the end of each block, participants were informed about their accuracy and were able to take a self-paced break.

2.2.4.3 Behavioral analysis

Our main hypotheses concern the EEG data and are not directly related to the behavioral performance pattern. However, as in previous studies using this protocol, we expected to observe a decrease in reaction time with target repetition (Carlisle et al. 2011; Gunseli, Meeter, and Olivers 2014). To test this, we performed a Bayesian paired sample t-test to compare reaction times of 1st and 5th old context target repetitions.

2.2.4.4 EEG recording and registered analysis

The electroencephalogram (EEG) was recorded from 32 sintered - AG/AgCl electrodes. The electrodes were positioned at International 10/20 System sites and mounted in an elastic cap using Brain Products actiCHamp (actiCHamp Plus, Brain Products GmbH, Gilching, Germany). The vertical EOG electrodes were located at 2 cm above and below the right eye, and the horizontal EOG electrodes were located at 1 cm lateral to the external canthi. We performed the analysis of the EEG data using MATLAB (*MATLAB* 2022), the EEGLAB toolbox (Delorme and Makeig 2004), and custom code. Trials containing ocular artifacts that are recorded by EOG, and EEG noise such as blocking, muscle noise, saturation, etc., were detected manually via visual inspection. Trials with such artifacts were excluded from further analysis. We applied a filter to EEG data by IIR Butterworth filter with a band-pass of 0.1-40 Hz using the pop_eegfiltnew.m function of EEGLAB. The online reference electrode was located in the right mastoid, and then the data was re-referenced offline to the average of left and right mastoids. Baseline period of 200 ms prior to stimulus onset was included in the ERP analysis.

The CDA was computed at P7/8, PO3/4, PO7/8, and O1/2 electrodes (Günseli et al. 2019; Ikkai, McCollough, and Vogel 2010; Vogel and Machizawa 2004; Vogel, McCollough, and Machizawa 2005) by subtracting the activity of ipsilateral channels from the contralateral ones relative to the target position between 400 to 1400 ms after target onset (retention interval). To test if new targets are stored in WM (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Gunseli, Meeter, and Olivers 2014; Reinhart, McClenahan, and Woodman 2016) , the CDA in new target trials were compared against zero using two one sample t-tests, one for new contexts and the other for old contexts. Next, to test if repeated targets are being handed off from WM to LTM (Carlisle et al. 2011; Gunseli, Meeter, and Olivers 2014; Reinhart, McClenahan, and Woodman 2016), we compared the 1st and the 5th target repetitions using a Bayesian paired-samples t-test. For this analysis, we used old context trials only. To assess if this difference showed a linear or a quadratic CDA trend through a target repetition series (Figure 2), a trend analysis with repeated measures ANOVA was conducted. Last and importantly, to assess whether a context change results in the targets stored in LTM to be reactivated in WM, we used a Bayesian paired samples t-test to compare the CDA in new vs. old context trials only for the 5th target repetition where a handoff to LTM is expected based on previous literature (Carlisle et al. 2011; Gunseli, Olivers, and Meeter 2014; Gunseli, Meeter, and Olivers 2014; Reinhart, McClenahan, and Woodman 2016).

2.2.4.5 Exploratory analysis

We calculated the N2pc, which is an index of attentional selection(Eimer 1996; Hickey, Di Lollo, and McDonald 2009). Similar to CDA, N2pc was calculated as a difference between contralateral and ipsilateral activity regarding the target position, time locked to the onset of the memory item. This difference was calculated between 250 ms and 350 ms based on visual exploration of our data and our previous study with a similar design (Senturk et al. 2023). Time-frequency analysis was conducted to explore the involvement of attentional processes in memory reactivation (Fukuda and Woodman 2017; Günseli et al. 2019). Bilateral and contralateral alpha-band suppression were analyzed in the time course between 500-1200 ms. The same channels with the CDA analysis (P7/8, PO7/8, and O1/2) were used in the calculation. We analyzed the power of frequencies between 4 and 50 Hz to see if the effects we observed were alpha band specific or propagated to other frequencies. To calculate bilateral alpha-band suppression, we defined our frequencies between 8-12 Hz (Günseli et al. 2019; Woodman, Vogel, and Luck 2012) on a logarithmic scale. For each frequency, a sinusoid (ei2ft) was created then these sinusoids were converted to morlet wavelets by being tapered with a Gaussian (n (e-t2/2s2; s is the width of the Gaussian; s = /(2f); denotes for number of cycles created for wavelet). We padded zero to the beginning and the end of our data as half of the length of our morlet wavelets. Our epoched data were rearranged as one continuous EEG data. Fast Fourier Transform (FFT) was applied to both the EEG and morlet waves. The dot product of the Fourier-transformed EEG data and Fourier-transformed morlet wavelet was calculated for each frequency. Then inverse FFT was applied to each dot product. With this procedure the EEG data became convoluted for each morlet wavelet. Then, we performed baseline normalization and decibel (dB) conversion. Each baseline was calculated by averaging the power activity between 500-200 ms before the memory item onset of all trials. The power activity in each trial was divided by this baseline and converted to dB. Then, for the analysis regarding the alpha band suppression, we averaged the dB values between 8-12 Hz, 400-1200 ms, over trials for each condition. We have chosen a slightly shorter time window compared to the CDA calculation to prevent probe related activity contaminating the power due to the temporal smearing caused by convolution.

A similar procedure was applied to calculate the contralateral alpha suppression. But for contralateral alpha suppression, the baseline was calculated between 500-200 ms before the location cue rather than the memory onset. Since the location cue was given before the memory representation, a lateralization can be expected in the baseline time window that reflects the expected attention (Ikkai, Dandekar, and Curtis 2016). This might result in disappearance of lateralization in the retention interval due to baseline removal with a lateralized baseline. This difference in baseline time range was applied to get a clear baseline without lateralization. This baseline normalization was applied to each condition separately, unlike the bilateral time-frequency decomposition. Then the power values from the selected channels (P7/8, PO7/8, and O1/2) that are contralateral to the target item position were subtracted from the ipsilateral channels (Günseli et al. 2019).

2.3 Results

2.3.1 Behavioral Results

2.3.1.1 Reaction times

First, we analyzed the reaction times of participants' responses. When the 1st and the 5th repetitions were compared, there was anecdotal evidence for no change in reaction times with repetition (old context TR1 vs old context TR5, BF10 = 0.669; t(21) = 1.597, p=.125). There was also anecdotal evidence for equal reaction times at the new and old context trials' first repetitions (BF10=0.225; t(21)= 0.132, p=0.896). Also, there was anecdotal evidence for an increase in RT with a change in context at the 5th repetition (BF10 = 1.536; t(21) = 2.164, p=.042). When we conducted a trend analysis with repeated measures ANOVA, repetition showed no linear contrast (t(105) = -1.357; p = .178).

2.3.1.2 Accuracy

For accuracy, analysis showed strong evidence for increase in accuracy with repetition (old context TR1 vs old context TR5, BF10 = 91.247;t(21)=-4.265, p<.001; linear contrast with repetition, t(105)=5.923, p<.001). But the accuracy didn't respond contextual changes, there was and anecdotal evidence for equal accuracy at the 5th repetition between change in context (M=.96, SD=.02) and old context (M=.96, SD=.02; BF10= 0.243; t(21) =0.432, p=.67)

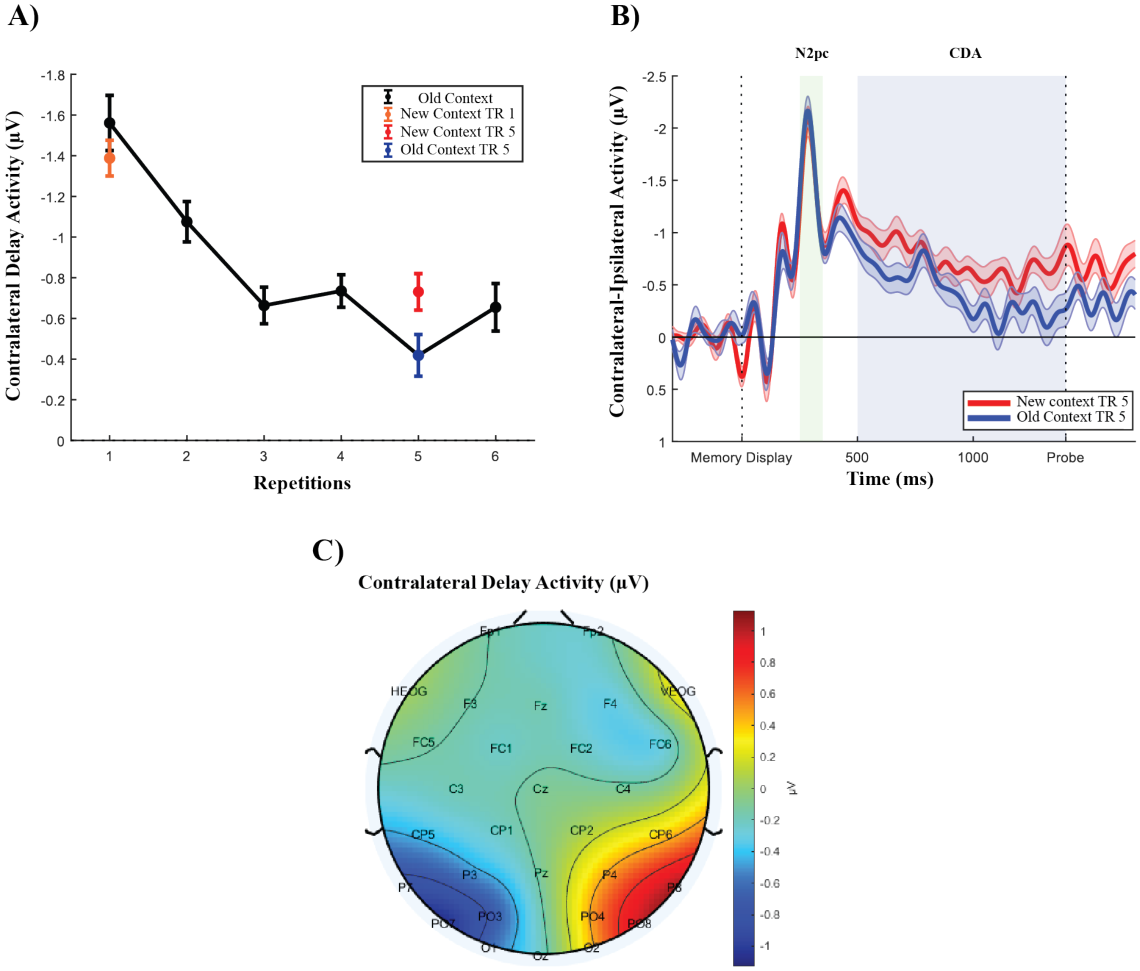
2.3.2 EEG Results

2.3.2.1 Contralateral delay activity

As depicted in Figure 2.2.A, We compared the CDA amplitudes of the 1st repetition trials against 0 to see whether there is a CDA when a novel object is presented. The 1st repetition trials' CDA values were more negative than 0 (old context, BF10=34470; t=-7.134, p<.001; new context, BF10=43375; t(21)=-7.252, p<.001). Then we compared the 1st and 5th repetition of old context trials to see transition of the item from WM to LTM. Results showed strong evidence that the CDA amplitude of the 5th repetition was different from the 1st (BF10=2406; t(21)=-5.815, p<.001), which suggests the representation of the target item was transferred to LTM with repetition of the same task and item (linear trend, t(105) =6.859, p<.001).

Then, we compared the 5th repetition trial regarding whether there is a change in context or not. When there was a change in background color, we observed strong evidence for a recovery in the CDA (BF10=8.858; t(21)=-3.131, p<.01; Figure 2.2.B). We can conclude that if there is a change in context the item is reactivated in WM.

Figure 2.2 Contralateral delay activity



A) CDA changes through repetitions. **B)** CDA and N2pc comparison between new and old context trials at the fifth repetition of the target item. **C)** Through retention interval, contralateral negativity on the scalp

2.3.2.2 N2pc

N2pc didn't show any changes regarding the contextual changes. However, with the first repetition, we observed a strong increase in N2pc (BF10=55.982; t(21)=4.033, p<.001) (Figure 2.3.A). After this increase, it didn't show any changes due to context changes (BF10=; 0.240 t(21)=0.401, p=.692).

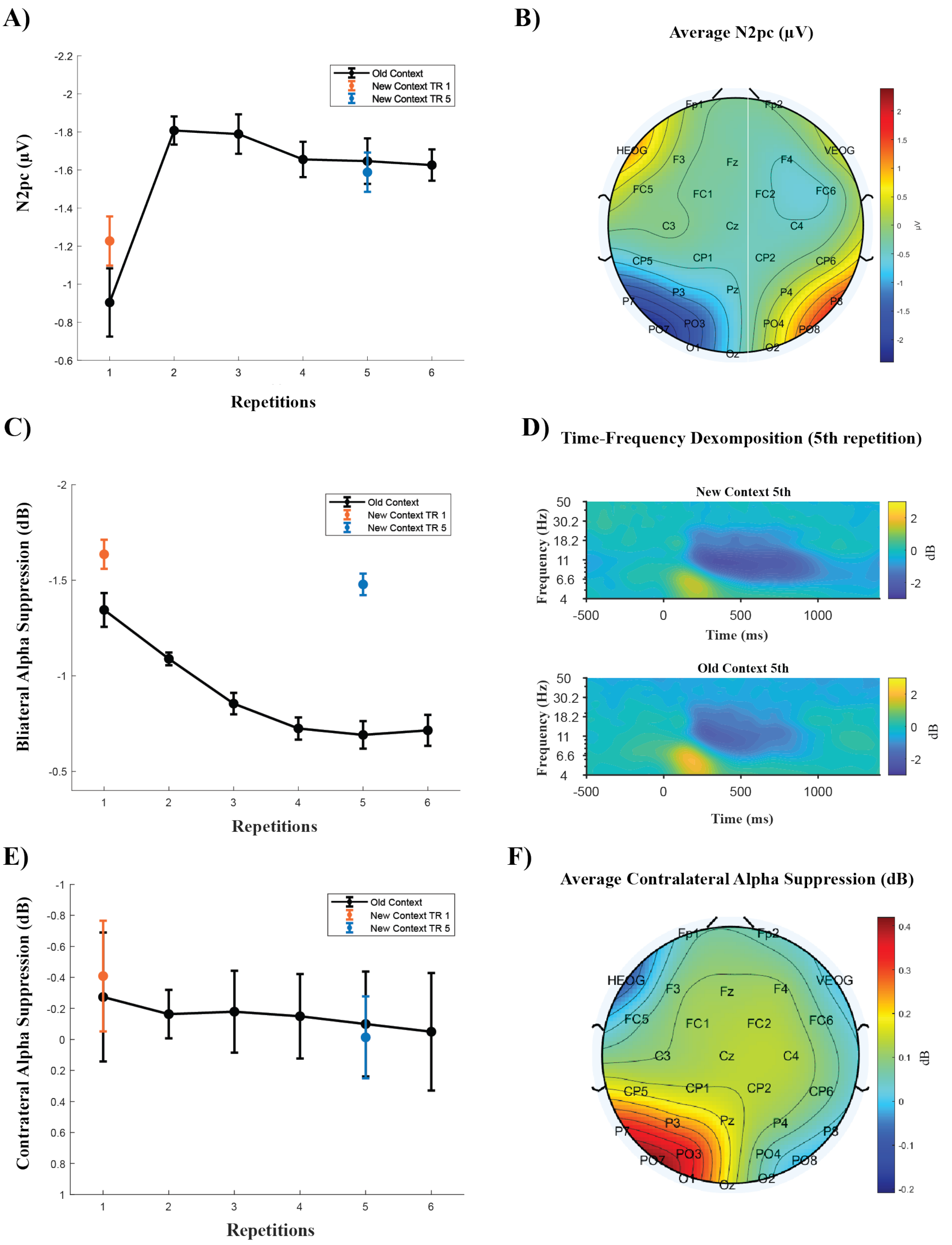
2.3.2.3 Alpha band suppression

Our time-frequency analysis showed that when we examine alpha-band suppression, we observe a very similar pattern with CDA (Figure 2.3.C) . When we compare the 1st repetition with the 5th in old-context condition, we see a decrease with the repetition of the same target (BF10=396.46; t(21)=-4.957, p<.001) and it is support by the linear trend observed with repetition (linear contrast, t(105)=8.023, p<.001). Then, the comparison between old-context and new-context trials at the 5th repetition shows that alpha band suppression recovers (BF=1830; t(21)=-5.683, p<.001) as we observed in CDA. These results suggested that overall attentional resources given were declined with repetition and recovered with a contextual change (Reinhart and Woodman 2014; Senturk et al. 2023). Also, this increase in alpha suppression is a sign of memory reactivation (Fukuda and Woodman 2017).

2.3.2.4 Contralateral alpha band suppression

We analyzed the spatial lateralization in the alpha band suppression regarding the object position (Figure 2.3.E). Alpha band suppression showed moderate evidence for no change regarding the repetition of the target or contextual changes (BF10=0.223, t(21)=0.048, p=.96).

Figure 2.3 Exploratory analysis



A-B) Changes in N2pc through repetitions and the illustration of the average N2pc. **C)** Bilateral Alpha Suppression through repetitions. **D)** Bilateral Alpha Suppression at the fifth repetition new vs. old context conditions. **E-F)** Changes in Contralateral Alpha Suppression through repetitions and the average Contralateral Alpha suppression.

2.3.3 EEG-Behavioral relations

We examined whether the reactivation in WM predicts any behavioral performance of the participants. To achieve this, we subtracted the CDA amplitudes at the 5th repetition old-context trials from the 5th repetition new-context trials. Similarly, we subtracted the reaction times and accuracies at the 5th repetition of old-context trials from the 5th repetition of new-context trials. Then when we checked whether the changes in CDA due to contextual changes predict any behavioral performance by analyzing correlations. CDA differences with contextual changes predicted neither a difference in accuracy nor in reaction times (CDA-RT, Pearson's r=-0.267, p=.23, CDA-Accuracy, Pearson's r=-0.087, p=.701).

2.4 Discussion

In this study, we examined whether task-irrelevant changes in context result in memory reactivation. There has been a well-studied effect of task-irrelevant context in LTM literature (Godden and Baddeley 1975; Tulving and Thomson 1973), but this relationship has not been investigated in WM studies. Considering that context affects the meaning of a task-relevant information and its relationship with the task in everyday life, we hypothesized that contextual changes reactivate the task-related information in WM even though the context and its change is irrelevant to the task.

Our results showed that novel targets were stored in WM, as indicated by a s CDA (Carlisle et al. 2011; Gunseli, Meeter, and Olivers 2014; Günseli et al. 2019; Vogel and Machizawa 2004). There was a decrease in the CDA amplitude across repetitions and the CDA was absent at the 5th target repetition which arguably reflects the transition of the target representation from WM to LTM (Anderson 1983; Carlisle et al. 2011; Logan 1988). Importantly, with a change in context (background color), the CDA was recovered. This result suggests that a change in task-irrelevant context elicits the reactivation of task-relevant memories.

Given the relationship between context change and memory reactivation, an important question is whether this reactivation is involuntary. We argue that our data supports so. Our cognitive systems use their resources in the most cost-effective ways (Mızrak and Oberauer 2021; Stokes 2015. For example, previous studies have shown that the neural cost of WM is avoided or diminished when, stimuli are presented for longer, thus can be recovered from perceptual input (Chota et al. 2023).. In our experiment, the reactivation regarding the contextual changes showed neither benefit in behavioral performance nor predicted it. Besides, the neural cost of this reactivation was observed as an increase in CDA and alpha band activity suppression. This metabolic cost in the absence of behavioral benefits suggests that memory reactivation might not be a strategic choice. In that sense, we propose memory reactivation that takes place due to contextual changes is involuntary.

What could be the reason behind a context-change dependent memory reactivation? Previously, Reinhart and colleagues found that memories are reactivated for tasks that provide instructions to aim for better performance (2014) or for higher reward (Reinhart, McClenahan, and Woodman 2016), suggesting that high stakes require stronger memory activation. On the other hand, using behavioral indices, Mızrak and Oberauer (2021) suggested that reactivated memories were mostly reserved to instances partly overlapping with past experiences, in line with the proposed role of WM to resolve proactive interference (Engle 2002). These studies match in their claims regarding WM to be specific to particular task settings - namely, high stakes and high proactive interference. On the other hand, we recently showed that repeated items are reactivated in WM if there is a change in task rules, not for a particular task setting itself. Here, we extend these findings to show that changes in task-irrelevant information also entails memory reactivation. Together with the results of Senturk et al. (2023), our results suggest that memory reactivation has a role in adaptation to novel settings.

If the reactivation of the memories reflects adaptive mechanisms, what adaptive functions does it serve? We propose two beneficial outcomes of memory reactivation elicited by contextual changes. One of them is hippocampal pattern separation. Similar memories are represented with similar neural patterns. But to prevent interference between similar representations, the representations of similar events are separated (or differentiated) in the hippocampus (Amer and Davachi 2023; O'Reilly and McClelland 1994; Yassa and Stark 2011). Although this theory focuses on episodic memories, here we argue that WM-driven processes might be crucial to achieve pattern separation. For instance, two mechanisms have an overlapping cortical region such as the CA3 subregion of the hippocampus is associated with pattern separation and the area is also involved in spatial WM (Kesner 2013 . Also, given that reinstated memories are stored in a transformed format (Favila, Lee, and Kuhl 2020; Sahan, Sheldon, and Postle 2020) , reactivation might serve as a medium to transform memory to achieve a separate pattern of activation to adapt new context. In our experiment, encountering the same item in a different context might signal that it is a distinct event, thus encouraging pattern separation, which might benefit from a neural reinstatement. Future studies can focus on the hippocampal driven pattern separation and its relationship with memory reactivation to better specify the role of WM in pattern separation.

Another mechanism that might necessitate the reactivation of the item in WM due to a change in context can be contextual binding in WM (Artuso and Palladino 2011; Borders, Ranganath, and Yonelinas 2022; Cai et al. 2022; Oberauer and Vockenberg 2009). This process achieves associations between context and the related content in WM. In previous binding studies, the context was manipulated as the target item's spatial position, color, or temporal property (when it is presented) (Artuso and Palladino 2011; Cai et al. 2022; Oberauer and Vockenberg 2009). This context association affected behavioral performance. For instance, (Oberauer and Vockenberg (2009)) showed that after an item is presented and replaced with another item, participants showed faster recognition of the item's reappearance if it is presented at the same place. They suggested that WM benefits this contextual association. In our study, the change in background color might be triggering the reactivation of the item in WM to achieve the binding of the content with the new context. Our design doesn't enable us to further explore this relationship. Because, our task doesn't necessitate participants to use context binding to achieve better performance, and doesn't enable us to observe if content and context are associated in representational space. Also, this might be due to filtering of context reinstatement regarding task demands in intraparietal sulcus (Fulvio, Yu, and Postle 2023). But future studies might explore if the reactivation predicts any benefit of contextual binding to see whether these two processes interact.

Contralateral alpha-band suppression did not differ across repetitions or contextual changes. Contralateral alpha suppression is studied as a reallocation of attentional resources in a spatial manner (Günseli et al. 2019; Woodman et al. 2022). In our study, it wasn't coherent with CDA and bilateral alpha suppression. One thing these results indicate is that there is a difference between the reallocation of attentional resources and WM storage. Some papers suggest that WM is the reallocation of endogenous attentional resources (Gazzaley and Nobre 2012; Kiyonaga and Egner 2013) . But we advocate WM is not only a different nomenclature of this reallocation, but it is also a separate mechanism. To increase the involvement of WM, bringing the item into more online representational space, overall attention investment increases with the WM storage indexes. But it doesn't mean that spatial attentional reallocation is also involved in this process.

To summarize, contextual changes trigger memory reactivation. The item that has been transferred to LTM with repeated storage is reactivated in WM upon a change in the task-irrelevant context (i.e., background color). Given the neural costs and absence of behavioral benefits, we argue that this reactivation is involuntary.

Although not beneficial in the current study, reactivation in WM may be beneficial in most daily life settings to adapt to novel settings. Our findings highlight that not only LTM but also WM is sensitive to context.

3. TOP-DOWN CONTROL OVER RHYTHMIC SAMPLING OF ATTENTION

3.1 Introduction

We perceive the world continuously, but our attention samples information rhythmically (for a review see Fiebelkorn and Kastner 2019; VanRullen 2016). Our attentional weight changes between alternatives in visual space in a rhythm. For instance, if the expected event is likely to occur in several possible places within the visual field, selective attention samples information from these areas by rhythmically changing perceptual sensitivity (Fiebelkorn 2022; Landau and Fries 2012; VanRullen 2016). What we mean by that is perceptual sensitivity will enhance and decrease for each possible area of expectation in rhythmic oscillations. In this study, we are examining whether the properties of these oscillations can be controlled in a top-down manner. To achieve this, we manipulated the context as the reliability of our expectation of an event occurring. And we hypothesized that a priori contextual information regarding the possibility of an event will affect the rhythmic properties of attentional sampling.

The rhythmic oscillations of perceptual sensitivity can be observed in behavioral performance (Chen et al. 2017; Fiebelkorn 2022; Landau and Fries 2012; Peters et al. 2021; Su et al. 2021). Landau and Fries 2012 used stimulus onset asynchrony (SOA) to show this association. In their experiment, participants were shown two drifting gratings on the screen. Their task was to detect a contrast decrement (target) that happened on a limited area of one of the gratings by choosing which grating that target occurred. One of the gratings was cued as a target location before the decrement happened in each trial, the decrement happened on either the cued or the non-cued grating. The decrement happened at a time point between 750 ms before and 1000 ms after cue onset in steps of 16.7 ms. They showed that the behavioral performance of participants oscillated as a function of SOA. Since the perceptual sensitivity changed over time, behavioral performance oscillated according to the coincidence of sensitivity with the timing of the target event. Their result showed attentional sampling oscillates theta-alpha band.

The behavioral oscillations were interpreted as an outcome of cortical oscillations (Busch, Dubois, and VanRullen 2009; Dugué, Marque, and VanRullen 2011). The rhythmic nature of sampling was associated with theta oscillations in the attention network (Fries 2023; VanRullen 2016). For instance, Busch, Dubois, and VanRullen (2009) showed that oscillations in change detection performance were phase-locked to the EEG oscillations in the higher theta range. Also, entraining these neural oscillations with transcranial stimulation methods can affect perceptual performance. In their study, Bree et al. (2021) showed that transcranial alternating current stimulation (tACS) can improve perceptual performance (speech perception in this case) but only its phase is defined by the phase relationship of EEG and stimulus presentation. Also, seeing similar attentional weight changes in internal resources such as WM (Peters et al. 2021) representations might support the idea that these oscillations in different mechanisms are resulting from hardwired oscillations .

External factors such as neural entraining can affect attentional oscillations. But can we control these oscillations in a top-down manner? There are limited studies focused on this aspect of the mechanism. Su et al. (2021) manipulated if the participants were rewarded with a task. When the reward was presented regarding task performance, the alpha inhibition emerged earlier at the cue location approx. 120 ms according to phase-frequency analysis. In another study, Chen et al. (2017), examined the effects of task difficulty on these behavioral oscillations. They manipulated task difficulty by QUEST procedure (Watson and Pelli 1983) (to achieve target contrast specific to each participant for standardizing accuracy in terms of task difficulty). Their result showed that if the task difficulty increases, the frequency of oscillations decreases. They interpreted this result as a consequence of the need to obtain more information in difficult versions by increasing the duration of enhanced perceptual sensitivity.

In this study, we focused on the reliability of the cue as a contextual feature of the task. We presented two placeholders and a central cue to show in which placeholder the target will appear. The target was a 45-degree tilted line, and participants were asked to determine which side the line was tilted. Target appeared with SOA, meaning that it appeared on one of the 42 steps of 16.7ms after cue onset. The cue reliability changed across blocks. In high cue reliability blocks the cue showed 80% correct place to target will appear, and in low reliability, the cue showed 65 % correct place of appearance. But to separate this effect from task difficulty like observed by Chen et al. (2017), we also used the QUEST staircase method (Watson and Pelli 1983) to change the contrast of the target due to performance. By doing so, we aimed at 70% accuracy regardless of cue reliability. This isolated the effect of reliability from task difficulty. We conducted a time-frequency analysis through our SOAs. We explored whether this a priori contextual information regarding the possibility of target appearance has affected any circular property of behavioral oscillations of attentional sampling.

Our preliminary results showed that there is an increasing trend in the frequency of sampling when the reliability of cue increases, and vice versa for the decreasing cue reliability. This study contributes to our understanding of how top-down control affects the rhythmic oscillations of attention. Also, this a priori information sets a context within the context definition specified by Stark et al. (2018). Therefore, these studies and design also show the effect of contextual features on the mechanism of sampling, which is one of the earliest stages of information processing.

3.2 Methods

3.2.1 Participants

5 female subjects (All female, Mage = 23.8) participated in this pilot experiment. All of the participants had normal and corrected-to-normal vision. The 4 subjects were Sabancı University students who volunteered or were granted course credits in return for their participation. We didn't exclude any participant from the study, we only excluded trials from further analysis due to our exclusion criteria (see Analysis section).

3.2.2 Ethics Statement

This study was conducted in line with the declaration of Helsinki and approved by Sabancı University Research Ethics Committee.

3.2.3 Stimuli

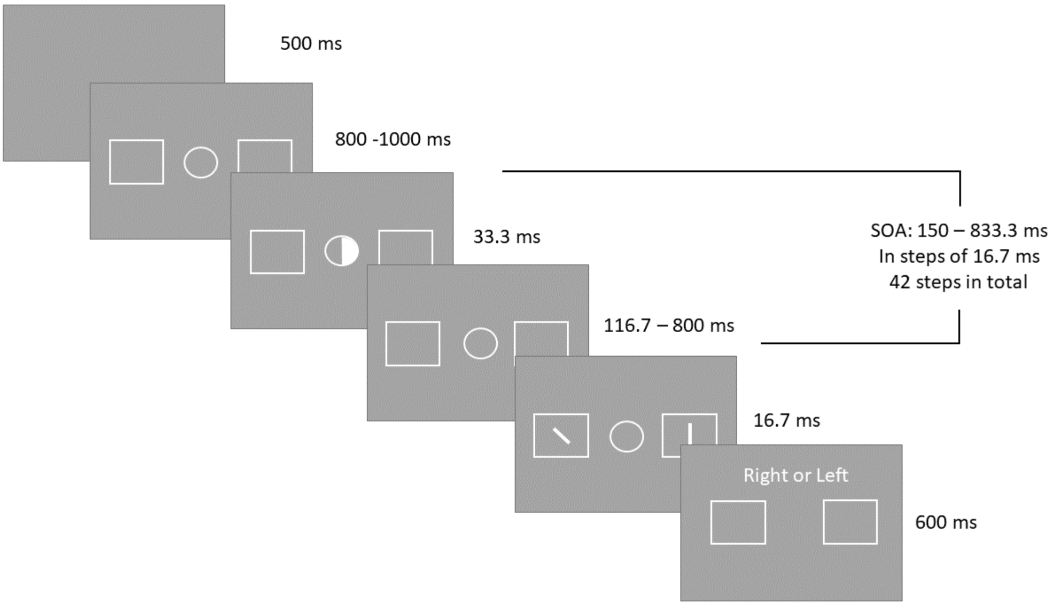
In each trial, participants were shown a white circle (diameter angle: 0.36°) in the middle of the screen as a fixation. Two white square boxes (each edge: 0.9°) appeared at each side of the circle as placeholders for the target. The distance between the center of each placeholder and the center of a fixation cross was 4.5° (Figure 3.1). The half of the fixation circle was filled white briefly as a cue, indicating the side of the target appearance. The target was a 45-degree tilted line (0.22°) which can appear in the center of either of the two placeholders. The target line was white. Its contrast was determined by the QUEST adaptive staircase procedure (Watson and Pelli 1983). The staircase procedure manipulated the target contrast throughout the experiment to achieve 70% accuracy for each participant for each condition. To achieve this, the contrast was recalculated based on the accuracy of all previous trials. All stimuli were presented on a 27 inch Screen. The screen's frame rate was 60 Hz. Participants responded by using a cable keyboard. The whole experiment and stimuli were designed and presented with Psychtoolbox (Brainard 1997) on MATLAB (*MATLAB* 2022). During the experiment, the eye movements of participants were recorded with SR Research Eyelink Portable Duo Eye Tracker.

3.2.4 Design and Procedure

3.2.4.1 Trial design

As depicted in Figure 3.1, each trial began with a blank gray screen for 500 ms. Then two placeholders and a fixation circle appeared first. After a jittered interval between 800-1000 ms, the right or left half of the fixation circle was painted white for 33.3 ms as an indication of the appearance of the target. In the valid cue trials, the target appeared on the side that the cue signs, and in the invalid ones, the target line appeared on the opposite side with the cue position. In each trial, the target appeared on one of the possible 42 SOAs of 16.7 ms intervals after the cue and appeared on the screen for 16.7 ms (which corresponds to a single frame of the screen). Another same-length straight line appeared in the opposite placeholder, to achieve the perceptual balance. Following the target's presence, participants were asked to indicate which side the target line was tilted to by the arrow keys of a keyboard as quickly as possible. If participants didn't respond within 2500 ms, the experiment continued with the next trial.

Figure 3.1 Illustration of experimental procedure



Each trial began with the presentation of the fixation circle and placeholders. The fixation circle cued the side where the target object would appear. The reliability of the cue varied between conditions. The target appeared on the screen with SOA. Participants were asked to respond as to which way the target line tilted.

3.2.4.2 Trial distribution & block design

The experiment consisted of 6300 trials in total. Due to the long design of the study, participants attended 3 sessions on different days. Each session had 28 blocks, and each block had 75 trials. For each session, half of the blocks were high cue reliability conditions, and for the other half, the reliability of the cue was low. Reliability condition changed halfway through each block, counterbalanced by which participant starts a session.. The starting reliability was counterbalanced across sessions and participants. High reliability blocks had 60 valid and 15 invalid trials with 80% reliability of the cue, and low reliability blocks had 45 valid and 30 invalid trials with 60% reliability.

The target was presented with SOA. After the presentation of the cue, a tilted line appeared in one of the 42 SOAs 16.7 ms apart from each other. There werea total of 150 trials for each SOA. The number of trials was the same for each SOA in every session.

3.2.5 Analyses

In the analysis, we used MATLAB built-in functions and functions from CircStat (Berens 2009) for circular analysis. First trials with RT's less than 150 ms and false answers were excluded. Then, RTs were averaged for each condition. That resulted in 42 averaged RT values across SOAs for 4 conditions (valid-high cue reliability, invalid-high cue reliability, valid-low cue reliability, and invalid-low cue reliability. Averaged RT values were sorted according to the order of SOAs for each condition, smoothed by averaging with the adjacent time bins, and detrended with a second-order polynomial (Fiebelkorn, Saalmann, and Kastner 2013; Peters et al. 2021; Re et al. 2019). After smoothing, 40 time-bins remained as SOA steps (the first and the last step weren't included in the analysis). To compare the main effect of the cue reliability we performed a Bayesian t-test between valid-invalid RTs for high cue reliability and low cue reliability.

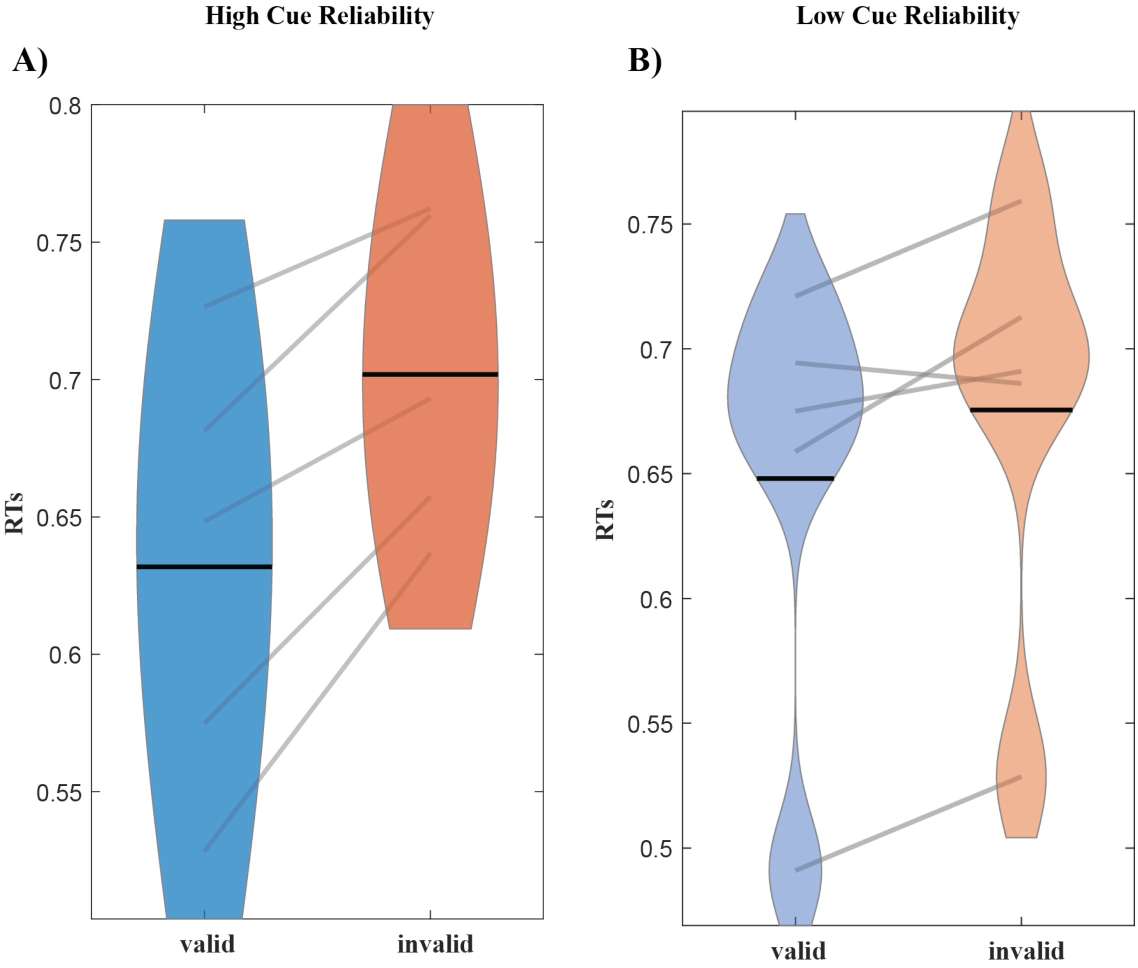
For time-frequency power analysis 40 SOA time range of each participant's each block Fast Fourier Transformed (with built-in function FFT of MATLAB). Then the absolute values of the FFT were squared to achieve power values. Power values for frequencies between 1.5 to 13.5 Hz (Peters et al. 2021) for each participant were averaged separately. For phase relationships, angular differences between valid and invalid trials were compared for high-reliability conditions cue and low-reliability cue conditions. These angular differences were presented in complex space, and lengths of the average vectors provided Phase Locking Values (PLV) (Lachaux et al. 1999), one for high cue reliability, and one for low cue reliability conditions.

For statistical analysis, 42 SOA of each participant's each condition were shuffled for 5000 permutations (Peters et al. 2021). Then, the same procedure was applied to this permuted data. It resulted in 5000 power matrices for 1.5-13.5 Hz and 5000 PLV vectors. We obtained the p values by calculating what percentage of the permuted results were higher than the power and PLV values of the real data. These p values were corrected for the false-discovery rate for each frequency bin of interest (Benjamini and Hochberg 1995; Peters et al. 2021). We accepted .05 as a significant p-value.

3.3 Preliminary Results

First, we conducted a Bayesian t-test between RTs of valid and invalid conditions to see whether the cue reliability was effective. Our preliminary results showed that in high-reliability conditions the RT difference between valid and invalid trials showed strong evidence (BF10 = 9.995; t = -5.280, p<.001). And for low cue reliability conditions, the difference showed moderate evidence (BF10 = 1.876; t=-2.55, p=.06).

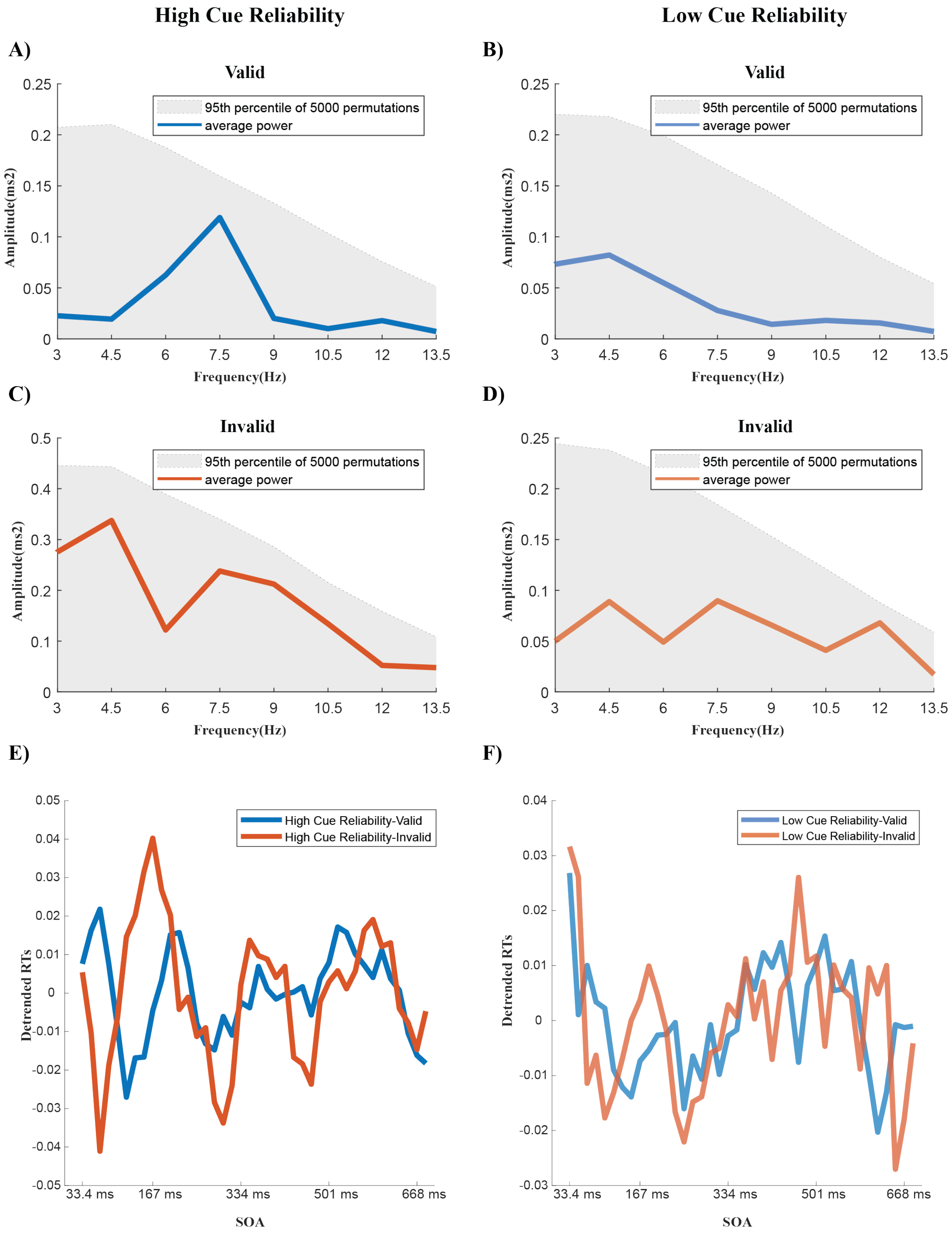
Figure 3.2 Averaged RTs across conditions



A) Averaged RTs of valid and invalid trials for High Cue Reliability condition. **B)** Averaged RTs of valid and invalid trials for High Cue Reliability condition. In both conditions RTs were slower for invalid cues.

For time-frequency analysis, we averaged all conditions to see if a power of any frequency reached significance by achieving a higher power value than the .05 of 5000 permutations. No frequencies showed such an effect at this point of data collection. Averaged amplitudes of power showed peaks at 4.5 Hz and 7.5 Hz. These frequencies were in line with the previous literature on behavioral performance oscillation being in theta range (Chen et al. 2017; Fiebelkorn, Saalmann, and Kastner 2013; Landau and Fries 2012; Re et al. 2019; Su et al. 2021).

Figure 3.3 Frequency powers and oscillations

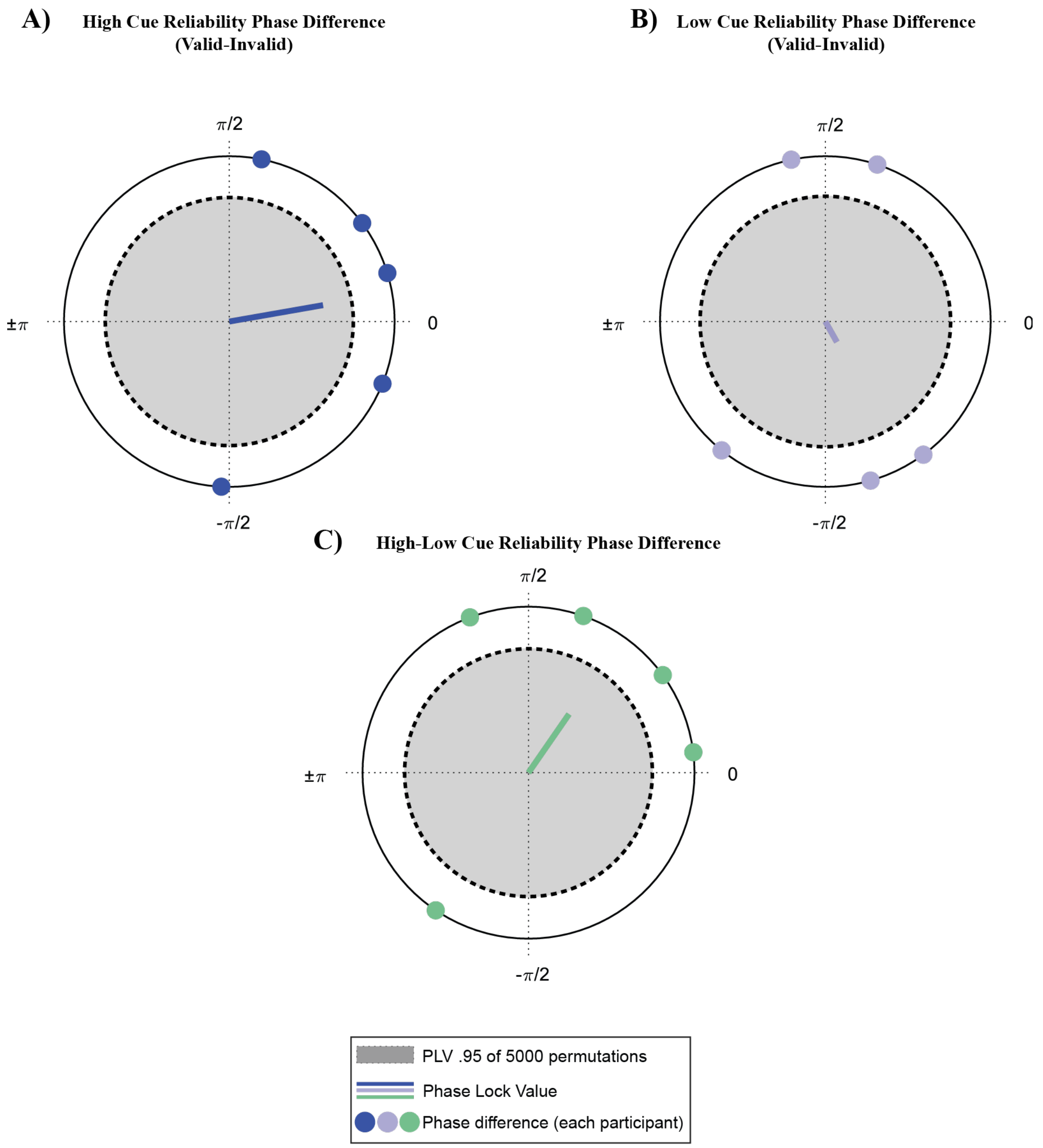


A-B-C-D) Illustration of frequency powers of each condition. **E-F)** Illustration of detrended RTs of each condition through SOA.

Then we examined the power relationships of conditions. No condition showed a significant power in any frequency (Figure 3.3). But for preliminary results, we investigated the peak frequencies of each condition. When the cue reliability was high, the TF power showed a peak at 7.5 Hz when the cue was valid, and at 4.5 Hz when the cue was invalid. And for low-reliability conditions, it peaked at 4.5 Hz for valid trials and 7.5 for the invalid ones (Figure 3.3).

As depicted in Figure 3.4, Following TF power analysis, we analyzed the power differences between conditions. To see the differences, we used 4.5 Hz and 7.5 Hz separately for phase analysis, since those frequencies were peak overall and for each condition. First, we calculated the angle for each condition, then we took the difference between valid and invalid condition angles for high-reliability and low-reliability conditions. We calculated PLVs for valid-invalid differences for high and low-reliability conditions. Then we compared those PLVs with the 5000 PLVs from permuted data. Neither condition could reach the level of .05 significance. We wanted to understand whether the difference between valid and invalid cases varied in reliability. For this, we obtained an average angle by subtracting the angle differences we calculated above and compared it with the permuted data. The average PLV didn't reach significance.

Figure 3.4 Phase relationships of valid and invalid trials across conditions



A-B) Illustrates the phase difference between the behavioral oscillations regarding valid and invalid cues. Colored dots shows individual phase differences for each participants. Length of the colored lines shows PLV for each condition. Gray shaded area depicts the .95 percentile PLVs of 5000 permutations. **C)** Illustrates the difference between high and low cue reliability conditions in terms of the shift between valid-invalid trials.

3.4 Discussion

In study, we examined the effects of the reliability of attentional priority cues on the properties of rhythms of attention.This Our preliminary results showed the average TF power peaked at the theta range (4.5 Hz and 7.5 Hz) similar to previous studies (Chen et al. 2017; Fiebelkorn, Saalmann, and Kastner 2013; Landau and Fries 2012; Peters et al. 2021; Su et al. 2021). For the high cue reliability conditions, the peak frequency shifted from 7.5 to 4.5 between valid to invalid trials. And the results were vice versa for low-reliability cue conditions. Any of these results were statistically meaningful. But the trends observed were in line with our hypothesis.

The frequency of attentional rhythms to cued and uncued positions were in opposite directions across reliability conditions. When the cue reliability was high, the rhythm of attention was higher on valid cue trials (7.5 Hz) compared to the invalid cue trials (4.5 Hz). This might be due to the less need to check the invalid side when the cue is more reliable. Likewise, we observed the opposite trend when the validity of the cue was low. The frequency of the attentional rhythm was higher on invalid (7.5 Hz) vs the valid cue (4.5 Hz) trials. As opposed to our interpretation of frequency shifts regarding task demands, Chen et al. (2017)claimed that a decrease in peak frequencies due to conditions may allow more information to be gathered about the target. Lower frequencies in attentional sampling may increase the time of enhanced sensitivity. In their study, they manipulated the task difficulty. Here, we equated the task difficulty by setting accuracies at the same level between participants and conditions using a QUEST staircase procedure (Peters et al. 2021; Watson and Pelli 1983). Then by manipulating cue reliability, we observed the opposite effect. We claim that our results can be explained by the motivation to get more information from the invalid trials, participants may sample at a higher frequency in invalid trials in the low-reliability cue condition.

These modulations in sampling might be an automatic process or intentional control. Since changes in rhythmic sampling might be sensitive to task demands, it can be an implicit strategy to adjust behavior to different environments. Our experimental design doesn't allow further investigating which of these scenarios are responsible for modulations of rhythmic sampling. Future research might explore these relationships by manipulating contextual features in quick changes (such as every 10-20 blocks). In that sense they can eliminate implicit strategy options by preventing adaptation to the task context within a short amount of time.

The frequency shifts between conditions might be affected by the properties of the contextual changes. Reward, task difficulty, and cue reliability as different contextual settings were shown to affect the sampling processing differently (Chen et al. 2017; Su et al. 2021). These effects were observed in TF and phase relationships at theta range. And in these studies, while task difficulty and cue reliability showed effects as shifts as peak frequencies, reward showed phase relationship effect. Together, these results might imply that different necessities of contextual settings affect different properties of attentional sampling.

Many studies suggest that the theta band oscillations in behavioral performance result from alpha band oscillations of the attentional network (Busch, Dubois, and VanRullen 2009; Fries 2023). These neural oscillations show dependency on behavioral oscillations (Bree et al. 2021). Can these contextual changes manipulate neural oscillations as well? Studies show that neural entrainment affects attentional performance, but this effect is predicted by the phase relationship of neural and behavioral oscillations (Bree et al. 2021). Also, EEG oscillations predict the phase of behavioral oscillations (Busch, Dubois, and VanRullen 2009). When we consider this interdependence, the adaptation in alpha band neural oscillations might be causing these changes in the properties of behavioral oscillations. If so, the effects of cue reliability might also have an effect on the alpha-band activity in the brain. Future studies that use electrophysiological measures can test this claim to inform the relationship between alpha-band neural activity, theta-band behavioral rhythms, and how top-down goals might modulate them.

As a limitation of our pilot study, in this present design, we aimed for 70% accuracy for all conditions. To achieve that we manipulated contrast through trials with the QUEST staircase procedure (Watson and Pelli 1983). This resulted in a barely visible target item when the contrast is lowered by the algorithm. Since this can increase the percentage of guesses in participants' responses, we decided to continue with a higher target accuracy of 85%. This will allow our staircase procedure to be stable around higher contrasts which will increase the accuracy of participants and reduce the guess rate.

To sum up, this study will continue by collecting data from participants until we reach our target sample size of 25, this number was calculated from studies with similar designs (Chen et al. 2017; Peters et al. 2021; Re et al. 2019; Su et al. 2021). And to reduce the guess rate in the study, the target accuracy of the QUEST staircase procedure will be increased to 85%. Our preliminary results didn't reach significance for any main analysis. But we showed some trends regarding the effects of cue reliability. And we claimed that these adaptive changes in attentional oscillations can manipulate different mechanisms to adapt to different contextual settings.

4. GENERAL DISCUSSION

In two studies, I examined the effects of context on two fundamental mechanisms of information processing, these are WM and attention. Results of the first study showed that task-irrelevant contextual changes resulted in memory reactivation in WM (Chapter 2). The second study (preliminary results) showed that contextual settings regarding the reliability of attention-directing cues might affect the frequency of attentional sampling of the external world (Chapter 3).

In this thesis, I inherited the context definition of Stark et al. (2018), extended some tenets, and aimed to show further categorization of the context as its relevance to the task. They defined context over its stability, grouping effect, and observable effects on behavior. Our contextual manipulations were stable over time. In the WM study, we set two background colors as context, these colors were consistent over time in terms of their visual features throughout the experiment (Chapter 2). Regarding cue reliability, the reliability conditions set consistent reliability between conditions it was 80% percent for high reliability and 60% for low, they remained stable over the experiment (Chapter 3). Also, our manipulation had a grouping nature. In the WM study, the context manipulated over repetition resulted in the repetition of the target item with the same context-created groups. Similarly in the attentional sampling experiment, the cue reliability manipulation was a grouping factor that enables the group trials within the block of the same reliability condition.

I extend the third tenet of context being observable in the behavior. Its effects can also be observable at the neural level due to our results. In our study, the change in context didn't show any meaningful change in behavioral performance, but its effects were observable within the neural measures. I suggest that especially if the context is not directly related to the experimental task itself, its effects might be unobservable at the behavioral level. Or the effect of context on behavior might not be observable within the scope of the experiment. For example, content-context bindings show benefits in behavioral performance (Logie, Brockmole, and Jaswal 2011; Oberauer and Vockenberg 2009), but the simplicity (or low difficulty level) of our design may not have enabled participants to use those associations to achieve better performance (see Chapter 2).

Furthermore, I categorize the context as task-relevant and task-irrelevant in this thesis. I suggest task-irrelevant contexts as well affect the processing of task-related information. In Chapter 2 we manipulated background color as task-irrelevant context and showed memory reactivation regarding context change. These changes in background color didn't affect any properties of the task itself or the object. Participants didn't need to track the changes in the background to achieve the delayed match to the sample task. But still, we observed similar effects with the contextual changes regarding the task, and reward (Reinhart and Woodman 2014) that participants directly engage. In light of these results, I suggest that we need to emphasize more the associations of stimuli that are unrelated to the task and behaviorally unobserved effects of these associations.

Also, when the context is task-related its effect might be mediated by the relationship between the contextual changes and the task's nature. This relationship can allow observing changes and effects resulting from task demands. In Chapter 3 we manipulated cue reliability as a contextual feature. In similar designs, different manipulations that can set a context had different effects from our preliminary results. Reward manipulations showed phase-related effects on attentional oscillations (Su et al. 2021), task-difficulty manipulation showed shifts in the frequency of rhythmic sampling (Chen et al. 2017), and we showed a trend in a shift on behavioral sampling on opposite levels with task-difficulty. Here these results can show that task-related context might affect the mechanisms of attentional sampling through how it is interacted with the task demands.

To sum up, in this thesis, I aimed to handle context as a feature stable over time, groups information, and its effects can be observable at a behavioral or neural level that is based on Stark et al. three tenets (2018). Also, I tried to categorize context as task-relevant and irrelevant. Showed that task-irrelevant features might also affect the processing of task-related information. And task-related changes might affect the related mechanism differently through its relationship with the task's design. And finally, since any information in nature exists in isolation, adding contextual features to experimental design and considering its association with the target information might increase the ecological validity as well (Galiñanes Plaza, Delarue, and Saulais 2019). In that sense, I suggest that memory-attention studies might focus on these associations more, and how different contextual settings interact with the task and the target information.

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