8-15-2023 11:00 AM

Neural Dynamics of Target Processing in Attentional Blink

Mansoure Jahanian, *Western University*

Supervisor: Mohsenzadeh, Yalda, *The University of Western Ontario*
Co-Supervisor: Joanisse, Marc F., *The University of Western Ontario*
Co-Supervisor: Wang, Boyu, *The University of Western Ontario*

A thesis submitted in partial fulfillment of the requirements for the Master of Science degree in Neuroscience

Abstract

The attentional blink (AB) phenomenon refers to the failure to report the second target (T2) if it appears 200-500 ms after the first target (T1) in a stream of rapidly presented images. The present study aimed to investigate the neural representations of target processing under conditions where AB does or does not occur. We recorded EEG and behavioral data while participants viewed a rapid sequence of natural object images embedded with two face targets presented at two lag conditions: lag 3 (targets were 252 ms apart) and lag 7 (targets were 588 ms apart). Consistent with AB, our behavioral results showed a lower T2 identification accuracy in lag 3 compared to lag 7. We then used multivariate pattern analysis (MVPA) of EEG data to extract the neural dynamics of target processing over time. Comparing the neural representations of targets in the two lag conditions, we found that T1 processing coincided with T2 processing, resulting in suppressed T1 and T2 late representations in lag 3, where AB happened, but not in lag 7, where there was enough time between the two targets. Our results also indicated that target representations were different between participants with a strong AB effect (blinkers) and those with a weak AB effect (non-blinkers). These findings carry significant implications for theories of attentional blink, highlighting the need for their extension in order to account for naturalistic paradigms and new findings.

Keywords: Attentional Blink, Multivariate Pattern Analysis, EEG, Attention, Vision

Summary for Lay Audience

In this study, we investigated a fascinating phenomenon called the attentional blink (AB), which occurs when people are unable to correctly identify a second target image (T2) in a rapid sequential presentation of images if it appears shortly after the first target image (T1). The objective of this study was to explore and compare how our brain processes targets during AB. To achieve this, we measured brain activity and collected behavioral data from participants while they observed a rapid sequence of object images containing two face targets. T2 was presented either with a short delay (lag 3: T2 is item 3 after T1) or a longer delay (lag 7: T2 is item 7 after T1) after T1.

Consistent with previous findings, we discovered that participants had lower accuracy in identifying T2 when it appeared shortly after T1 (lag 3) compared to when there was more time between them (lag 7). To better understand the underlying neural dynamics of the attentional blink, we employed a technique called multivariate pattern analysis on the brain data. This analysis allowed us to examine how the representations of target processing in the brain evolved over time. By comparing the neural representations of T1 and T2 in the two lag conditions, we observed that T1 processing interfered with T2 processing, leading to diminished late representations of both targets in the lag 3 condition, where AB occurred. In contrast, in the lag 7 condition, where there was a greater temporal gap between the targets, this interference was not observed, and the representations of both targets were relatively preserved. These findings challenge current theories of attentional blink, as they cannot be easily explained by existing models.

Overall, this study provides valuable insights into how our brains process multiple targets in rapid succession, shedding light on the attentional blink phenomenon. Understanding these mechanisms can enhance our understanding of how the human brain perceives the ever-changing visual world around us.

Acknowlegements

I would like to express my gratitude to my supervisors Dr. Yalda Mohsenzadeh, Dr. Marc Joanisse, and Dr. Boyu Wang for their invaluable guidance throughout my research journey. Their knowledge, insightful feedback, and constant encouragement have been instrumental in shaping my research and ensuring its quality. I would like to thank my advisory committee members, Dr. Marieke Mur and Dr. Laura Batterink for their insights on my project. I am also deeply thankful to my lab members for their collaboration and countless hours of meaningful discussions. Their assistance has significantly contributed to the success of this project.

Lastly, I extend my deepest appreciation to my parents, my beloved sisters, and my friends for their unwavering encouragement and love. Their constant belief in me has been a tremendous source of motivation and strength. Their understanding, encouragement, and presence in my life have provided the emotional strength necessary to overcome challenges and persevere. I am profoundly grateful for their unwavering support and for always being there for me.

Contents

List of Figures

List of Appendices

Chapter 1

Introduction

1.1 Visual attention

In the blink of an eye, the surrounding environment bombards our brain with an overwhelming influx of visual information, exceeding the brain's capacity for simultaneous processing. Yet, remarkably, we understand the visual world without investing much effort. This feat is possible with a process that selects relevant information and filters out irrelevant information to help us perceive what we see. Visual attention is the key to this process, as it helps our brain selectively interpret the important parts of the visual information and ignore others by focusing on certain aspects of the visual scenes (Carrasco, 2011). With this selective capability, attention enables us to perform efficiently in spatial visual searches and pinpoint desired targets among a multitude of distractors in mere fractions of a second (Treisman and Gelade, 1980). Even during the sequential presentation of items in spatially overlapping locations, we are able to identify and distinguish a specific target from distractors when each image is presented for only a few milliseconds (Potter et al., 2014; Mohsenzadeh et al., 2018). However, with this rapid presentation, it becomes challenging to identify subsequent targets that appear closely in time. It is thus fascinating to explore the reasons behind this temporal limitation and discover ways to optimize our cognitive processes over time. In this context, studying the temporal limitations of visual attention can provide valuable insights.

1.2 Attentional blink

To study how visual attention works in response to fast visual presentations, researchers have used the rapid serial visual presentation (RSVP) (Hoffman et al., 1983; Schneider and Shiffrin, 1977). In an RSVP paradigm, several visual stimuli appear sequentially at the same spatial location, typically the center of the screen, and each very briefly (e.g., for around 100 ms per image). One or more targets that are visually different from other items are embedded in the sequence. Early investigation into the temporal limitations of visual attention using RSVP revealed that once two targets were presented in rapid succession, the identification of the first target disrupted the identification of the second target for a subsequent duration of around half a second (Broadbent and Broadbent, 1987), a phenomenon which is now known as attentional blink (AB). The attentional blink phenomenon happens when participants fail to correctly report two target images in rapid succession if the second target (T2) occurs within 200 to 500 ms of the first target (T1).

Raymond et al. (1992) were the first to introduce the term "attentional blink". In their study, many trials containing a series of black alphabet letter stimuli embedded with one white letter as the first target were presented to the participants at the rate of 100 ms per stimulus. Some trials contained the letter ”X” as the second target. Participants were asked to identify the first target and the presence of the letter "X" subsequent to the first target. They found that in the trials where T1 was reported correctly, T2 reporting accuracy was impaired significantly when T2 was presented within 200 to 500 ms after T1. Moreover, they showed that the attentional blink phenomenon is a deficit in our attention system rather than a sensory limitation since the identification of T2 was improved when participants were asked to ignore T1.

Given the good temporal resolution of the human attention and visual system, the presence of such a temporal limitation is intriguing. Therefore, many studies have investigated different aspects of attentional blink and tried to find out the underlying mechanism of this attentional deficit. The commonly used attentional blink paradigm is an RSVP at the rate of around 100 ms per item with two target images. The position of the second target relative to the first target is called lag; for example, lag 3 means that T2 is the third item after T1. During a rapid series of stimuli with two targets where each stimulus is presented for approximately 100 ms, when T2 is presented at lag 2 (200 ms inter-target interval), lag 3 (300 ms inter-target interval), and lag 4 (400 ms inter-target interval), participants exhibit significantly low performance in reporting T2, indicating the occurrence of attentional blink in these short lag conditions. However, as the lag condition increases to lag 5 (500 ms inter-target interval), lag 6 (600 ms inter-target interval), and beyond, participants' performance in reporting the second targets improves, suggesting the absence of attentional blink in longer lag conditions (Raymond et al., 1992; Einhäuser et al., 2007; Tang et al., 2020). The following section provides an overview of the two main categories of theories explaining the underlying mechanism of attentional blink. Additionally, relevant research conducted to investigate attentional blink is discussed.

1.3 Theories of the attentional blink

One theory of attentional blink that was presented by Raymond et al. (1992) is the inhibition model. They suggested that attentional blink occurs because of a mechanism that inhibits the processing of post-target stimuli in order to reduce physical feature confusion (such as color) between targets and distractors. They further explained that there are some attentional gates that open to allow the first target to be identified, but close immediately afterward to prevent interference from subsequent stimuli until the identification of the first target is complete. They assumed that this process takes about 500 milliseconds, corresponding to the attentional blink period.

However, in the subsequent years, Chun and Potter (1995) provided results that could not be explained by the inhibition model. In their experiment, participants were asked to find two black letters (targets) in a stream of black digits distractors, meaning that the targets were chosen physically similar but categorically different from the distractors. They observed that AB occurred even when there were no physical feature differences between T1 and the first distractor after T1. This led Chun and Potter (1995) to propose a two-stage model of attentional blink, which suggests that a stimulus passes two stages of processing to be identified correctly. In the first stage, a stimulus activates its stored conceptual representation, allowing for rapid recognition of most items in an RSVP. However, this information is temporary and can be replaced by subsequent stimuli. In the second stage, stimuli that are relevant to the task are further processed and consolidated into working memory. According to this model, AB occurs because of the limited capacity of the second stage, which causes the second target to wait until the first target is processed and encoded into working memory. Similar models and theories have since been proposed to explain attentional blink (Jolicœur and Dell'Acqua, 1998; Potter et al., 2002; Dehaene et al., 2003). All of these studies propose the limited capacity feature of target processing which prevents T2 from consolidation in working memory when it is tied up with T1 consolidation. Consequently, theories of central capacity limitations have dominated the field for about a decade (Martens and Wyble, 2010).

The turning point came with a study conducted by Di Lollo et al. (2005). They conducted an experiment with two cleverly designed conditions. In the first condition (uniform condition), participants were asked to identify three consecutive black letter targets (T1, T2, T3) in a stream of black digit distractors. In the second condition (varied condition), the middle target letter was replaced by a digit distractor (T1, D, T3), and participants were asked to report both letter targets and the middle digit. In the uniform condition, participants had no difficulty in reporting T3 correctly, which contradicted the idea that the attentional blink occurs due to a depletion of attentional resources for the previous targets. However, the reporting accuracy for T3 decreased in the varied condition, when the second target was a digit instead of a letter. To explain these results, Di Lollo et al. (2005) proposed that AB arises from a temporary loss of control over a specific attentional set rather than a resource limitation. Thus, when the first item after T1 was from the same category as T1, all targets were processed efficiently; on the other hand, when the first item after T1 was chosen from a different category, AB occurred.

Furthermore, many studies provided evidence that the magnitude of the AB effect can be reduced by manipulating the experimental design, providing additional evidence in opposition to the limited capacity theories. For example, a task-irrelevant visual motion or flicker can attenuate AB effect (Arend et al., 2006). Also, it has been demonstrated that if a second target is preceded by a distractor that shares a feature such as color with the second target, the AB can be significantly reduced (Nieuwenstein et al., 2005). These findings have sparked new discussions on whether the attentional blink is caused by limited processing resources or inefficient attentional control since limited-capacity models struggle to explain why the performance of reporting the second target improved in Nieuwenstein et al. (2005) study while there was no difference in the first target reporting performance, as well as why third target performance is not impaired in Di Lollo et al. (2005) study. As a result, newer studies provide support for the hypothesis of the dysfunction in attentional control instead of the limited capacity model (Olivers et al., 2007; Olivers and Meeter, 2008).

One of the recent studies in the line of work supporting the attentional control theories is the ”boost and bounce theory of attentional blink” proposed by Olivers and Meeter (2008). According to this theory, AB is a consequence of the dysfunctional gating of information into working memory. They proposed that the process of working memory involves an input filter that enhances the processing of stimuli that match the targets and inhibits distractor stimuli. Thus, during a rapid presentation of stimuli with two targets, the input filter inhibits the distractors presented before T1 to prevent them from accessing working memory. When T1 is presented, it is attentionally enhanced, allowing it to gain access to working memory. The first distractor after T1 receives a strong attentional boost due to its proximity to T1; however, the attentional enhancement of a distractor triggers a strong suppression or bounce of subsequent stimuli for around 500 ms, preventing distractors from entering working memory. This suppression will prevent T2 to be attentionally enhanced and thus cause the attentional blink.

The new contradictory findings mentioned above motivated studies to investigate the interaction between attentional allocation and temporal processing to gain insight into the underlying processes of the AB (See Yao and Zhou (2023) for a review of these studies). However, the mechanisms involved in the attentional blink phenomenon have yet to be discovered.

1.4 ERP analysis of attentional blink

In order to study the neural mechanisms underlying the attentional blink with a high temporal resolution, researchers have used electroencephalography (EEG) to monitor the brain activity of participants while they performed an attentional blink task. EEG provides a high temporal resolution, meaning it can capture brain activity with great precision in time. Thus, it is well-suited for studying rapid processes in the brain that occur in the order of milliseconds. One approach to contrast EEG responses in different conditions is the event-related potential (ERP) analysis.

ERPs show small voltages in the brain in response to specific stimuli (Sur and Sinha, 2009; Blackwood and Muir, 1990) and they are computed by averaging EEG signals time-locked to the onset of a target. ERPs consist of sequential peaks and dips, known as components that are identified based on their polarity (positive or negative) and order of occurrence. For example, P3 (or P300), a well-known ERP observed after the detection of a target, is a positive peak that appears around 300 ms after the target onset. The key benefit of ERPs is that they enable researchers to track the neural processes that take place after the onset of specific stimuli or events and provide a continuous measurement (Zivony and Lamy, 2022). ERP analysis will provide high temporal resolution information that results in a more comprehensive understanding of neural processes underlying behavior when integrated with behavioral results.

The first two ERP components after a target onset during a rapid presentation of images are P1 and P2 which indicate the early perceptual processing of the target. Most studies reported no significant changes in either P1 or P2 after T2 onset, when AB happens (short lag conditions such as lag 2 or lag 3) in comparison to when AB does not occur (longer lag conditions such as lag 7 or lag 8) (Vogel et al., 1998; Batterink et al., 2012; Kranczioch et al., 2003). This indicates that AB does not affect low-level perceptual processes (Zivony and Lamy, 2022).

The next component that is associated with attentional engagement is N2pc (N2-posterior-contralateral). The N2pc component usually arises between 180-300 ms after the onset of a stimulus over the posterior regions of the brain (Zivony and Lamy, 2022). It is characterized by a larger amplitude in electrodes positioned contralateral to the target's location in the visual field than those located ipsilateral to it. Consequently, the N2pc can only be detected when the targets are presented laterally in the visual field. Attentional blink studies showed that the N2pc component is reduced in shorter lags compared to longer lags (Pomerleau et al., 2014; Verleger et al., 2009). These findings might suggest that the attentional engagement of the target is impaired but not completely prevented during attentional blink.

The next component which has been studied the most is P3. The P3 is a positive deflection that occurs approximately 300-500 ms after the onset of a stimulus over midline EEG channels (such as Fz, Cz, or Pz). It is believed that P3 reflects processes related to target encoding in working memory. Many studies showed a clear lag effect on the P3 amplitude (Dell'acqua et al., 2003; Sessa et al., 2007; Vogel and Luck, 2002). As one example, Vogel and Luck (2002) conducted an experiment consisting of multiple trials of rapid series of black letters embedded with T1, a black digit, and T2, a white letter. Participants were instructed to report whether T1 was an odd or even number and whether T2 was the letter "E". They observed that in the lag 3 condition, the P3 component after the onset of T2 was fully suppressed. They also showed that when T2 was not masked with distractors, the P3 component was delayed in lag 3 (short lag) but not in lag 7 condition (long lag).

Limited capacity theories can explain the suppressed or eliminated P3 component, as they argue that the second target cannot reach working memory. On the other hand, attentional control theories can explain the results related to both impaired P3 and N2pc components through the disruption of attention. Both theories agree that the attentional blink does not occur in the initial stages of processing which might explain why P1 and P2 components are intact during attentional blink. Overall what we understand from ERP studies is that AB starts to appear around 200 ms after the onset of T2; nonetheless, there is limited neural evidence for attentional blink and it is relatively inconsistent.

While ERPs provide valuable information about the timing of neural activity, they have limited ability to capture the complex and simultaneous patterns of neural activity that underlie higher-order cognitive processes such as attention. Moreover, although ERPs can capture the neural responses after a simple stimulus, ERP components can overlap in time making it difficult to separate different components in multi-stage processes, especially in an RSVP task where the processes of targets and distractors are overlapping in time.

1.5 Multivariate pattern analysis of attentional blink

Another approach to investigate the neural dynamics of target processing over time is the multivariate pattern analysis (MVPA) of EEG data. MVPA is a broad category of techniques for studying neuroimaging data over space (fMRI) and/or time (EEG and MEG). What distinguishes these techniques is that the relationships between multiple variables (voxels in fMRI data and channels in MEG/EEG data) are considered, rather than treated as independent measurements (Grootswagers et al., 2017). One of the popular applications of MVPA is decoding analysis. In neuroimaging, the term decoding refers to the prediction of a cognitive process or experimental condition from brain data. MVPA can detect subtle differences in the temporal pattern of EEG activity that cannot be captured by ERP analysis and can be used to decode the neural representations of target processing based on these patterns.

A few recent studies used MVPA to study attentional blink (Meijs et al., 2019; Alilović et al., 2021). In Meijs et al. (2019) experiment, participants viewed several rapid sequences of white alphabet letters with a green letter as the first target and the letters ”D” or ”K” randomly as the second target. Participants were asked to report both targets. Their results indicate that the identity of T2 (D or K) can be decoded using MVPA of MEG signals. Alilović et al. (2021) designed an RSVP stream using alphabet letters as distractors and digits as targets. Similarly, they calculated targets’ and distractors’ neural representations using MVPA of EEG data. Moreover, they separated the trials into two groups: ”T2 seen” where T2 was reported correctly, and ”T2 unseen” where T2 was reported incorrectly. They observed that the early processing of T2 did not change significantly in seen and unseen responses.

While these studies (Meijs et al., 2019; Alilović et al., 2021) have successfully utilized multivariate pattern analysis to explore the neural dynamics associated with the attentional blink phenomenon, important questions remained unanswered in this area of research. For instance, it is unclear how neural representations differ when participants are presented with natural stimuli that resemble real-world visual scenes, as opposed to the commonly used letters and digits. Naturalistic paradigms are more complex compared to traditional paradigms; thus, delving into the study of these paradigms not only enables us to explore the differences in the AB effect between the two stimuli contexts but also facilitates the expansion of AB models to encompass these intricate stimuli. Additionally, while neural representations of correct and incorrect target responses have been compared, neural representations of target processing across different lag conditions have not been thoroughly investigated. Addressing the differences caused by lag conditions is important in elucidating the temporal dynamics of target processing in attentional blink which happens during the short inter-target intervals. The present study aimed to address these questions and provide valuable insights into the neural mechanisms underlying attentional blink. Answering these questions contributes to a deeper understanding of how attention operates in complex visual environments and rapid events, which may enhance our understanding of human cognition.

1.6 Study objective

The current study has two main aims. First, investigating the neural representations of target processing in an attentional blink paradigm when targets and distractors are natural stimuli rather than alphabet letters and digits traditionally used in attentional blink studies. By employing naturalistic stimuli, this study aimed to examine neural responses that are more representative of real-world scenarios. The second aim is to compare the neural representation of target processing under conditions where attentional blink does or does not occur, short lag and long lag conditions respectively. Thus, a comparison was conducted between the target representations in lag 3 (short lag) and lag 7 (long lag).

To address these aims, an attentional blink paradigm was designed using rapid series of object images embedded with two face targets, where each image was presented for 84 ms. EEG and behavioral data were collected while participants viewed multiple trials of the RSVP task, and they were asked to report both target faces at the end of each trial. MVPA of the EEG data was used to investigate the temporal dynamics of neural representations for target 1 and target 2 processing in lag 3 (short lag) and lag 7 (long lag) conditions. Specifically, a support vector machine (SVM) classifier was trained to decode the neural activity patterns associated with each target in each lag condition over time.

Moving forward to chapter 2, it offers a comprehensive exploration of the methods used in this study, encompassing all the necessary details. Chapter 3 delves into the presentation of the results. Finally, the last chapter is dedicated to a discussion, offering insights and interpretations of the findings in a broader context.

Chapter 2

Methods

2.1 Participants

Thirty-five healthy participants (17 female; age range: 18-35; mean = 22.8; STD = 4.2) took part in the experiment. Three were excluded from the analysis due to their low performance (less than 50% in first target identification accuracy) in the behavior task for a final sample of 32 participants. All participants were right-handed and had normal or corrected-to-normal vision, they signed a consent form prior to the experiment and received compensation for their participation. The study and all the procedures were approved by the Western University Health Sciences Research Ethics Board (HSREB) team. The ethics approval letter is attached to Appendix B.

2.2 Procedure

Participants viewed multiple rapid series of natural object images and they were asked to identify two face target images embedded in the stream of distractor images. Following the stream, two questions were presented consecutively to participants to report target images by pressing a button.

2.3 Design and stimuli

Target images were chosen from 16 face images (8 women and 8 men) from the Flickr Face HQ dataset (Hebart et al., 2019) (Figure 2.1 A), and distractors were chosen among 220 object images chosen from THINGS object concept and object image database (Karras et al., 2019). Face images were chosen from a variety of ethnicities to reduce the effect of participants' ethnicity. All face images displayed smiling facial expressions and forward gaze. Each image was converted to grayscale and resized to 220*220 pixels using MATLAB functions. Luminance matching was applied to all distractor images using the SHINE MATLAB toolbox (Willenbockel et al., 2010). The stimuli were presented using MATLAB Psychtoolbox (Pelli and Vision, 1997; Kleiner et al., 2007) on a 30-inch Dell monitor with 1200*1200 pixels resolution and a refresh rate of 59.95 Hz. Participants were seated 70 cm away from the monitor, and the stimuli covered 5 degrees of visual angle centrally on a gray background on the screen.

Each trial began with a 600-800 ms fixation (uniformly distributed) followed by a rapid series of 15 images (13 distractors and 2 targets) each presented for 84 ms. The first target was either item four or item six in the stream and the second target was item three or item seven after the first target, resulting in two different lag conditions, lag 3 and lag 7. There were other items after T2 to mask the second target. At the end of each trial, after a delay of 600-800 ms (uniformly distributed), participants identified T1 and T2 respectively among 4 options with a button press (Figure 2.1 B).

Each participant completed 22 runs. In each run, all 16 target images were randomly presented as T1 and T2, without repeating the same image for both targets. The same pair of images were used in both lag 3 and lag 7 conditions; therefore, each run contained 32 trials and the whole experiment session contained 704 trials. Prior to the experiment, participants viewed all target face images, each for 1 second, and did a practice run of 32 trials to get familiar with the task.

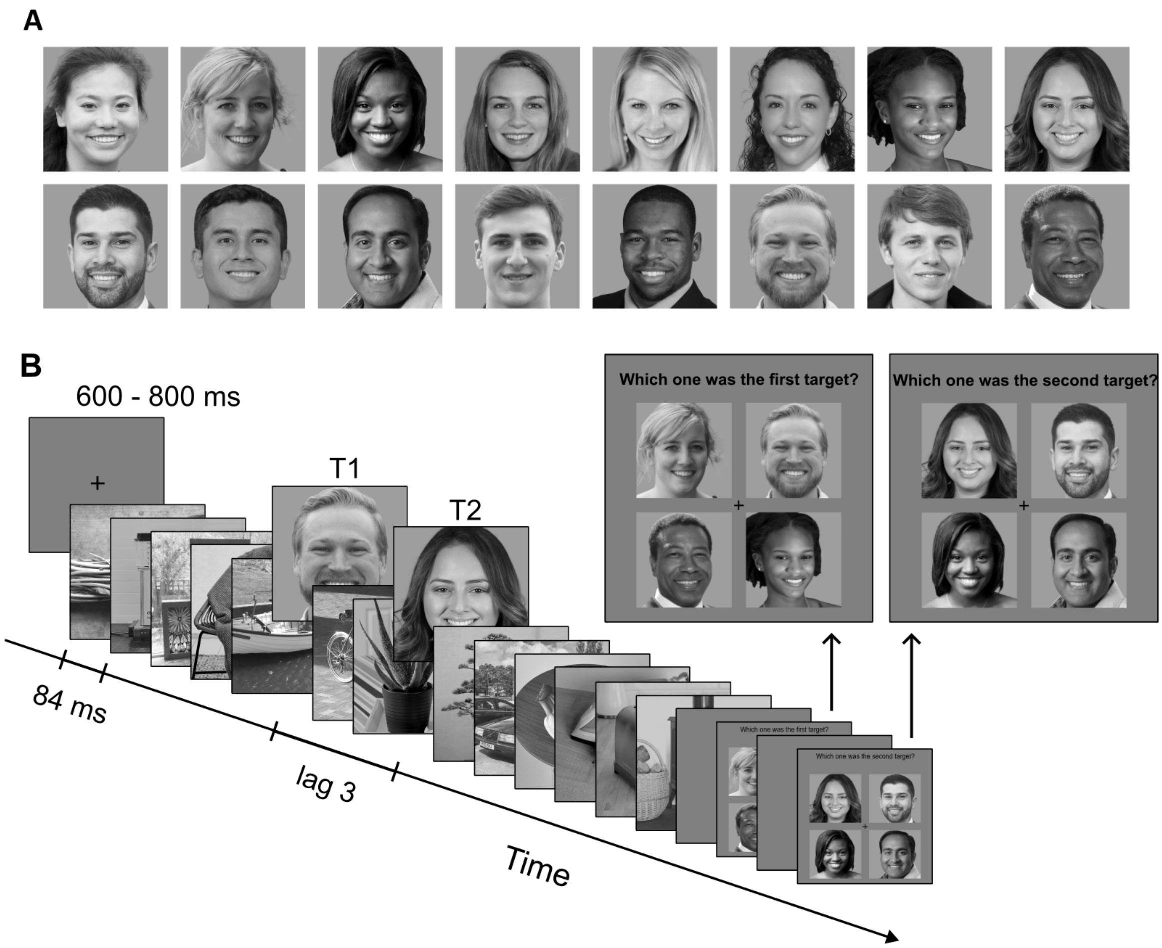

Figure 2.1: Stimulus set and experiment design. **(A)** Face target images. Targets were chosen from 16 face images, 8 women and 8 men. Face images were chosen from different ethnicities, but they shared the same facial expression. **(B)** The structure of each trial. Each trial started with a random fixation for 600 - 800 ms followed by 15 items: 2 targets and 13 distractors. Target images were randomly chosen from panel A images and distractor images were randomly chosen from 220 natural object images. Each item (target or distractor) could be presented once in a trial. T1 was presented randomly as item 4 or item 6 in the series and T2 was randomly presented at lag 3 or lag 7, each on half of the trials. At the end of each trial, after a random delay of 600 - 800 ms, participants were asked to report T1 and T2 respectively between four options.

2.4 EEG recording

The experiment was conducted in a sound attenuated dimly lit room designed for EEG experiments. Continuous EEG was recorded using a 64-channel Biosemi Active-Two system fitted with active-amplified electrodes. Data were recorded at a sampling rate of 2048 Hz and all electrode impedances were kept below 20 kΩ.

2.5 Preprocessing

EEG data preprocessing was performed using the Brainstorm MATLAB toolbox (Tadel et al., 2011). The data was filtered with a 0.5-30 Hz band pass filter and downsampled to a sampling rate of 512 Hz. Bad channels were removed if they were outliers in the power spectral density graph. Eyeblink and eye movement artifacts were corrected by Picard ICA (Makeig et al., 1996). The data was segmented into two groups of trials with respect to the onset of T1 and T2 (-200 ms to 1000 ms) with 200 ms pre-stimulus baseline correction. The trials containing excessive movement artifacts were rejected manually, and the trials with incorrect T1 responses were excluded as well.

2.6 MPVA: Decoding analysis

For each target in each lag condition, trials were labeled by their target face images. There were a maximum of M = 22 repetitions for each of the 16 target faces. Using 64 EEG channels, each time point t (from -200 to 1000 ms with 512 Hz sampling rate) at each trial included a pattern vector of 64 measurements. Using a pairwise support vector machine (SVM) classifier, we decoded the pattern vectors of each two target images at each time point (Chang and Lin, 2011). The classification accuracies for all time points were averaged over pairs resulting in decoding accuracy time series (Figure 2.2).

In more detail, to calculate the decoding accuracy time series for T1 in the lag 3 condition, all trials with T1 onset and the lag 3 condition were grouped together and each trial was labeled by the face image that was presented. Then for each time point, we performed pairwise SVM classification on EEG pattern vectors. To improve the signal-to-noise ratio, M pattern vectors of each label were divided into five folds, and pattern vectors within each fold were averaged, resulting in five input observations per face target image and a total of 80 (16*5) input observations for the classifier (each contained one EEG pattern vector as input features at time point t). Using the leave-one-out cross-validation method, four averaged pattern vectors were assigned as the train set, and one as the test set. The cross-validation process was repeated 100 times with random assignments of pattern vectors into averaged folds. The output pairwise classification accuracies were then averaged over all pairs to calculate T1 decoding accuracy, at time point t, in the lag 3 condition. The same process was performed to calculate T1 decoding accuracy in lag 7 and T2 decoding accuracy in the two lag conditions. Decoding analysis was done separately for each participant and then averaged over all participants. The averaged decoding accuracies for all participants over time were obtained to trace the neural dynamics of T1 and T2 processing in lag 3 and lag 7 in EEG data (Mohsenzadeh et al., 2018).

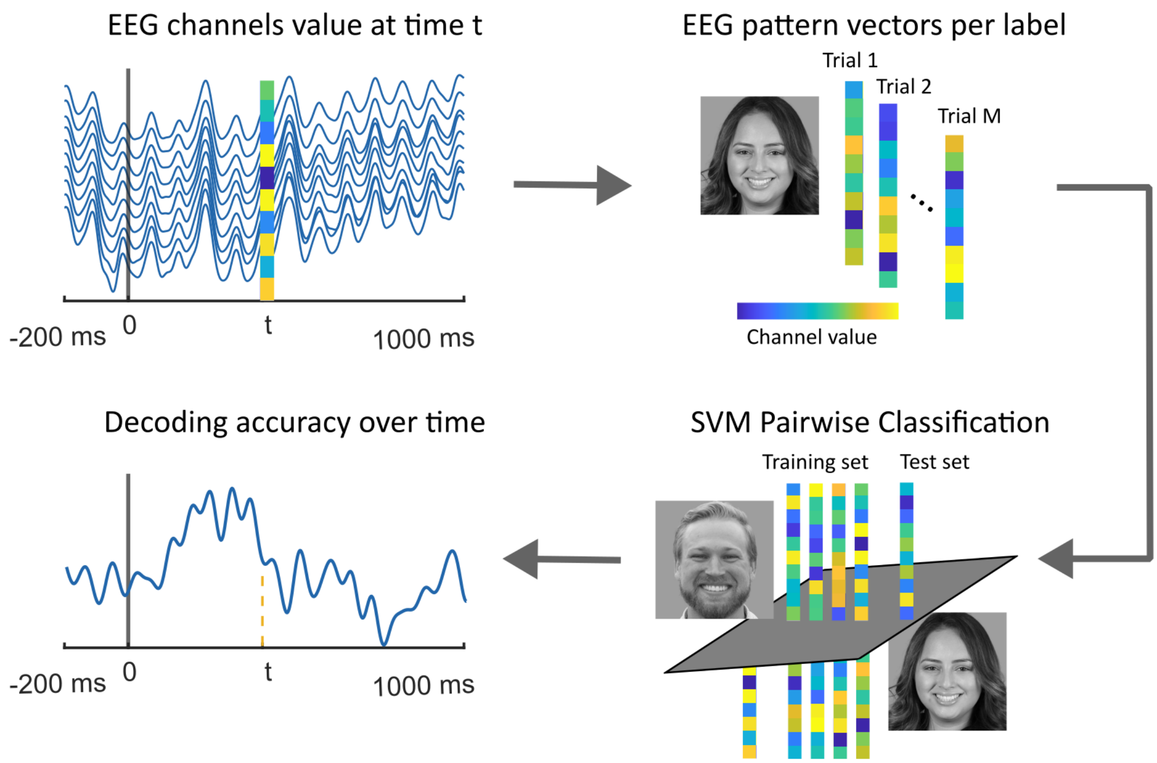

Figure 2.2: Multivariate pattern analysis of EEG data. For each participant, we segmented the EEG data into trials of 1200 ms, -200 ms to 1000 ms with respect to the target onset. Each EEG pattern vector was the 64 EEG channel values at time point t of each trial, and each target image was presented in M=22 trials, resulting in a maximum of M EEG pattern vectors per target image (label) at time point t. An SVM classifier was then used to do pairwise classification between EEG pattern vectors of all possible pairs of target images at time point t. Classification accuracy at time t was calculated using leave-one-out cross-validation. Pairwise classification accuracies were averaged over all possible pairs at each time point to calculate the decoding accuracy time series.

2.7 Significant interval duration in decoding accuracy time series

For statistical assessment of the significant interval duration in the decoding accuracy time series (the time interval that the decoding accuracy was significant), we performed bootstrap tests. 32 participants were bootstrapped 1000 times with substitution and each time the significant interval duration for the decoding time series was calculated using cluster correction. To find whether there was any lag effect in the duration of the early significant interval in the decoding accuracy time series, we calculated 1000 samples of difference between lag 7 and lag 3 significant interval duration for both T1 and T2. This resulted in an empirical distribution of duration differences for each target. We evaluated the p-value as the proportion of bootstrap samples that were less than zero.

2.8 MVPA: Temporal generalization analysis

To look at the stability of the neural representations over time, we extended the SVM classification procedure using a temporal generalization approach (Mohsenzadeh et al., 2018; Meijs et al., 2019; King and Dehaene, 2014). We trained the SVM classifier on time point t and tested it on all time points. To visualize a temporal generalization map, we used a 2D Matrix with the x-axis denoting training time and the y-axis testing time. More specifically, for all pairwise classifications, we trained the pairwise SVM classifier on time point t1 and tested it on time point t2. The averaged classification accuracy over all pairs shows the [t1, t2] element of the temporal generalization matrix (map). To reduce calculation time and visualize the temporal generalization maps better, time points were limited to -100 to 800 ms with respect to the onset of the target.

2.9 Correct versus incorrect T2 responses

To evaluate the difference between correct and incorrect T2 responses in lag 3 condition, we separated all the trials into two groups of correct and incorrect based on whether T2 was identified correctly. We then conducted pairwise classification between correct and incorrect labels to calculate the decoding accuracy time series for T2 responses. Since the number of correct and incorrect trials were different, we randomly chose N trials from the bigger group (N is the number of trials in the smaller group) before averaging the trials within each input fold to make sure there was the same number of trials in both the correct and the incorrect group. We performed the bootstrapping 1000 times, ensuring that the signal-to-noise ratio was similar for all input folds. The decoding accuracy time series for correct versus incorrect T2 responses in lag 3 condition were calculated by averaging pairwise classification accuracies over bootstrap repetitions.

2.10 Separating participants into blinkers and non-blinkers

To separate participants into two groups of blinkers and non-blinkers, for each participant we calculated the difference between T2|T1 performance in lag 7 and lag 3. Based on the histogram of the T2 performance difference between lag 7 and lag 3 we set a threshold (threshold = 3%). The chosen threshold was greater than the standard error of T2|T1 reporting accuracy. If the difference was greater than the threshold the participant was a blinker, otherwise the participant was a non-blinker. We found 13 non-blinkers and 19 blinkers among 32 participants.

2.11 Statistical analysis

Statistical inference of MVPA analysis relied on clustered-based non-parametric statistical tests (Maris and Oostenveld, 2007). We performed permutation-based cluster-size inference for statistical assessment of decoding accuracy time series and temporal generalization maps. The null hypothesis was set at a 50% chance level. To find the significant time intervals (clusters), the time series corresponding to participants were randomly sign-flipped and averaged 10000 times (permutations) to generate null distributions at each time point. By applying a cluster-defining threshold, significant time points were calculated and adjacent time points were grouped into clusters. The null distribution of maximum cluster sizes was estimated by finding the maximum cluster size of each permutation. Then, by applying a significance threshold, corrected significant clusters were calculated.

In all decoding analyses, we used 10000 permutations, 0.05 cluster defining threshold, and

0.05 significance threshold. In temporal generalization analysis, we used 10000 permutations, 0.01 cluster defining threshold, and 0.05 significance threshold.

Chapter 3

Results

3.1 Behavioral performance reveals attentional blink

We calculated the participants' average accuracy of reporting T1, and T2 given T1 had been reported correctly (T2|T1) for the two lag conditions (Figure 3.1 A). We observed a significant difference in T2|T1 accuracy between the two lags using a two-tailed paired-sample t-test (N=32 participants; lag 3 accuracy: mean=70.59%, SE=2.22%; lag 7 accuracy: mean=75.75%, SE=1.84%; $t(31) = 4.9,\ p < 0.0001$). This, in line with previous studies, indicated that AB occurred in our study (Raymond et al., 1992). Moreover, there was a significant increase in T1 accuracy in lag 7 compared to lag 3 (N=32 participants, lag 3 accuracy: mean=84.92%, SE=1.52%; lag 7 accuracy: mean=88.29%, SE=1.38%; $t(31) = 6.5,\ p < 0.0001$). This finding is similar to earlier studies highlighting that T1 reporting accuracy can vary at different lag conditions (Olivers and Nieuwenhuis, 2006).

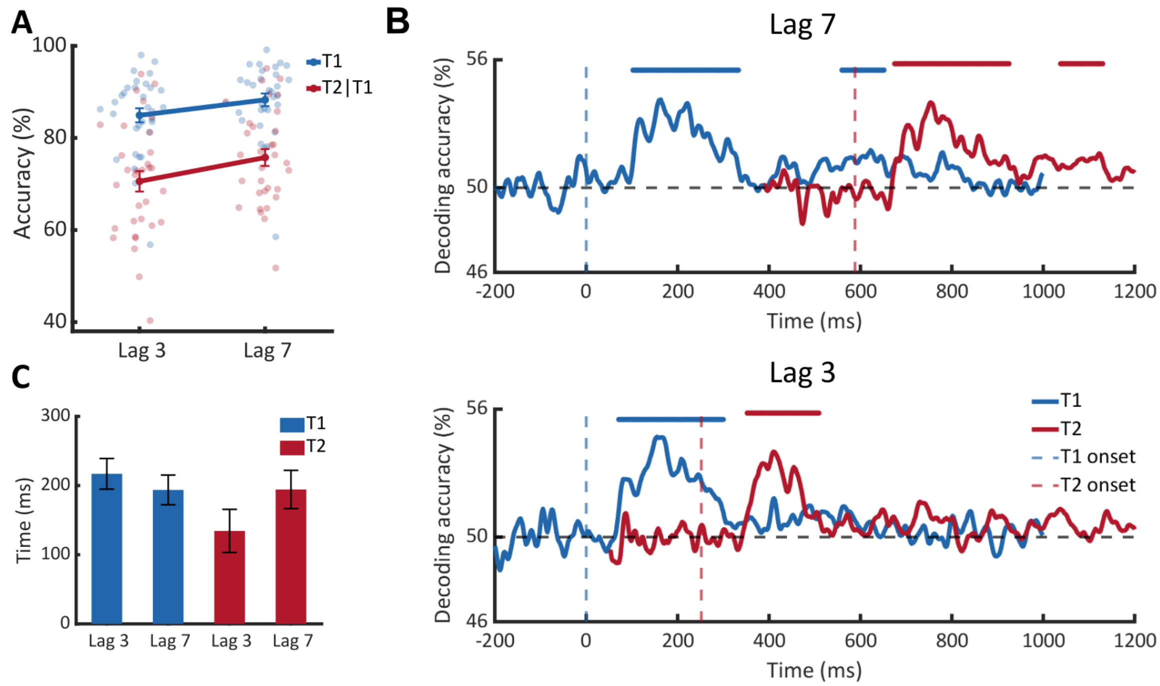

Figure 3.1: Behavioral and decoding analysis results. **(A)** Accuracy of reporting targets for the two lag conditions. T1 reporting accuracy is shown in blue, and T2|T1 (T2 given T1 identified correctly) reporting accuracy is shown in red. Circles show each participant's reporting accuracy. Error bars indicate standard error (SE). There was a significant effect of lag in T1 accuracy (N=32 participants, two-sided paired-sample t-test, $t(31) = 6.5$, $p < 0.001$) and T2|T1 accuracy (N=32 participants, two-sided paired-sample t-test, $t(31) = 4.9$, $p < 0.001$). **(B)** Decoding accuracy time series. Decoding accuracy time series of T1 (blue) and T2 (red) are shown in lag 7 (upper graph) and lag 3 (lower graph) conditions. The vertical dashed lines show the onset of T1 (blue) and T2 (red). The horizontal dashed line shows a 50% chance level. The lines above the graphs are significant intervals that were calculated using one-sided permutation tests and corrected with cluster correction (N=32 participants; cluster defining threshold $p < 0.05$, corrected significance level $p < 0.05$, 10000 permutations). **(C)** Significant interval duration in decoding accuracy time series for T1 (blue) and T2 (red). Error bars indicate standard deviation (STD). There was no effect of lag in the duration of the early significant interval of T1 decoding accuracy (N=32 participants, two-sided hypothesis test with bootstrapping, 1000 permutation, $p = 0.8$) or T2 decoding accuracy (N=32 participants, two-sided hypothesis test with bootstrapping, 1000 permutation, $p = 0.08$).

3.2 Neural representations of target processing depend on the lag between targets

Next, we aimed to determine if the neural representations of target processing exhibit a similar pattern as the behavioral results. To compare the neural representations of target processing in short and long lag, we calculated the decoding accuracy time series for T1 and T2 in lag 3 and lag 7 respectively (Figure 3.1 B) by performing SVM pairwise classification on EEG pattern vectors of target images (See Methods section 2.6 for more information). It is worth reiterating that all trials with incorrect T1 responses were excluded prior to the multivariate pattern analysis.

In lag 7, decoding accuracy increased significantly as early as ~102 ms after the onset of T1 and dropped to chance level (%50) after ~232 ms. The early rise in decoding accuracy indicated that the target identity can be decoded from the EEG data, and neural responses were resolved at the level of individual faces (Mohsenzadeh et al., 2018). After 400 ms of the T1 onset, decoding accuracy rose again indicating that T1 processing had continued for a longer period of time (as long as ~600 ms after the T1 onset). At around 674 ms (~86 ms after the onset of T2), T2 decoding accuracy started to increase significantly, while T1 decoding accuracy dropped to the chance level. The early rise in T2 decoding accuracy took ~250 ms, and then decoding accuracy decreased to chance level. At around 1000 ms after T1 onset, T2 decoding accuracy rose again, indicating T2 further processing similar to what we saw in T1 decoding accuracy time series.

The decoding accuracy time series of both targets presented two distinct stages of processing. The early processing occurred approximately 100 to 300 ms after the target onset, while the late processing happened after 400 ms. This is consistent with previous studies suggesting that there are two stages of processing for a target (Chun and Potter, 1995). The early stage happens as early as 100 ms after target onset, while the second stage of processing starts later and extends for a longer time. Furthermore, few studies observed the two distinct processing stages using MVPA (Meijs et al., 2019; Alilović et al., 2021).

What we observed in lag 3 was different. In lag 3, T1 decoding accuracy rose significantly at around 72 ms after the T1 onset and dropped to chance level after ~228 ms. The early rise in decoding accuracy of T2 was observed significantly after ~100 ms of T2 onset and the significant interval (the time interval that the decoding accuracy was significant) took around 156 ms before T2 decoding accuracy dropped to chance level. The early rises in T1 and T2 decoding accuracies were similar to the early rises we observed in T1 and T2 decoding accuracy time series in the lag 7 condition, and it showed the discrimination of neural responses at the level of individual face images in the brain. In contrast, there was no significant time interval in either T1 or T2 decoding accuracy after 500 ms of T1 onset. This suggested that in the lag 3 condition, the subsequent processing of T1 and T2 was inhibited, preventing the targets from progressing to the later stages of processing.

Comparing targets decoding accuracy time series in lag 3 and lag 7 conditions, first, we observed that the first significant interval of T1 decoding accuracy was similar in lag 7 and lag 3 conditions (lag 7 significant interval duration: 232 ms; lag 3 significant interval duration: 228 ms); however, the first significant interval of T2 decoding accuracy was higher in lag 7 in comparison to lag 3 condition (lag 7 significant interval duration: 250 ms; lag 3 significant interval duration: 156 ms). To find out whether there was any significant difference between the early rise duration in lag 3 and lag 7 conditions, we performed bootstrap tests to calculate the duration of the significant interval for each target in each lag condition (See Methods section 2.7 for more information). We observed no significant lag effect in the duration of the significant interval of T1 or T2 decoding accuracy (Figure 3.1 C) (N=32 participants, number of permutations=1000, T1 lag 3 significant interval duration: mean=216.99 ms, STD=22.15 ms; T1 lag 7 significant interval duration: mean=193.68 ms, STD=21.47 ms; $p = 0.8$ not significant), (N=32 participants, number of permutations=1000, T2 lag 3 significant interval duration: mean=134.33 ms, STD=31.23 ms; T2 lag 7 significant interval duration: mean=194.31 ms, STD=27.64 ms, $p = 0.08$ not significant). This finding in line with previous studies indicated that attentional blink does not have much effect on the early processing of targets (Zivony and Lamy, 2022; Meijs et al., 2019; Alilović et al., 2021). Our second and novel finding proposed that in lag 3 condition, the condition that attentional blink happened, T2 early processing coincided with T1 later processing, resulting in suppressed T1 and T2 late decoding accuracy. Nonetheless, in the lag 7 condition, where there was enough time between two targets, a late rise in decoding accuracy of both T1 and T2 can be seen, showing that targets were further processed in this condition.

Together, these results suggested that the early stages of target processing (reflected by the first rise in decoding accuracy time series) remained intact in the lag 3 condition (short lag condition). However, the subsequent processing (indicated by the second rise in decoding accuracy time series) was inhibited in lag 3 compared to the lag 7 condition (long lag condition).

3.3 Temporal generalization analysis confirmed the effect of lag on target representations

Temporal generalization analysis enables us to delve deeper into how visual information is transferred over time. Thus, instead of training and testing the classifier on the same time point, we trained SVM classifiers on one time point and tested them on all other time points to calculate the temporal generalization maps of T1 and T2 in lag 3 and lag 7 conditions (Figure 3.2). Similar to our observation in decoding analysis, in both lag conditions, significant decoding accuracy for T1 and T2 started to appear as early as 100 ms of target onset indicating that the individual target face images were decoded using EEG data.

In lag 7 condition, we observed a narrow diagonal pattern in T1 temporal generalization map from ~100 ms to ~300 ms (Figure 3.2A). The diagonal decoding pattern demonstrated a rapid sequence of distinct neural processes that evolved over time (King and Dehaene, 2014; Mohsenzadeh et al., 2018). Later in time, an off-diagonal square-shaped pattern can be observed in the temporal generalization map of T1. This pattern appeared to be weaker compared to the earlier time; however, it was significantly above the chance level (50%) between ~500 to ~600 ms after the target onset. The square-shaped pattern reflected that the decoding was extended in time and the neural representations of target processing were more sustained in this stage in contrast to the early stages where the neural representations were transient (Meijs et al., 2019). Upon examining the diagonal of the temporal generalization map for the second target in lag 7 condition, a consistent trend became evident (Figure 3.2 B). T2 decoding accuracy increased as early as ~100 ms after the target onset and then declined after approximately 200 ms. In the later stages, a square-shaped decoding pattern can be observed, which exhibited significance around 500 to 600 ms after the target onset showing the extended processing of the second target.

In the lag 3 condition, we observed a narrow diagonal pattern in the temporal generalization map of both T1 and T2 early in time (100 ms to 300 ms) (Figure 3.2 C, D), similar to what we found in the lag 7 condition. However, the decoding pattern was smaller and more limited to the diagonal for the second target. We could not see any significant square-shaped pattern in the temporal generalization maps later in time which indicated that the later processing of T1 and T2 in lag 3 was suppressed. In particular, the processing of T2 appeared to be more suppressed compared to T1 due to its narrower decoding pattern in the temporal generalization map.

Comparing lag 7 and lag 3 temporal generalizations maps of T1 and T2, we found that the early processing of targets happening between 100 ms to 300 ms of target onset was similar between lag 3 (AB condition) and lag 7 conditions. However, the later processing was suppressed in lag 3, but not in lag 7 as a broader decoding pattern can be seen in lag 7 condition for both targets. These findings are consistent with what we found in the decoding analysis (Results section 3.2), confirming that the early target processing remained unchanged regardless of lag condition, but higher-level processing was inhibited during attentional blink.

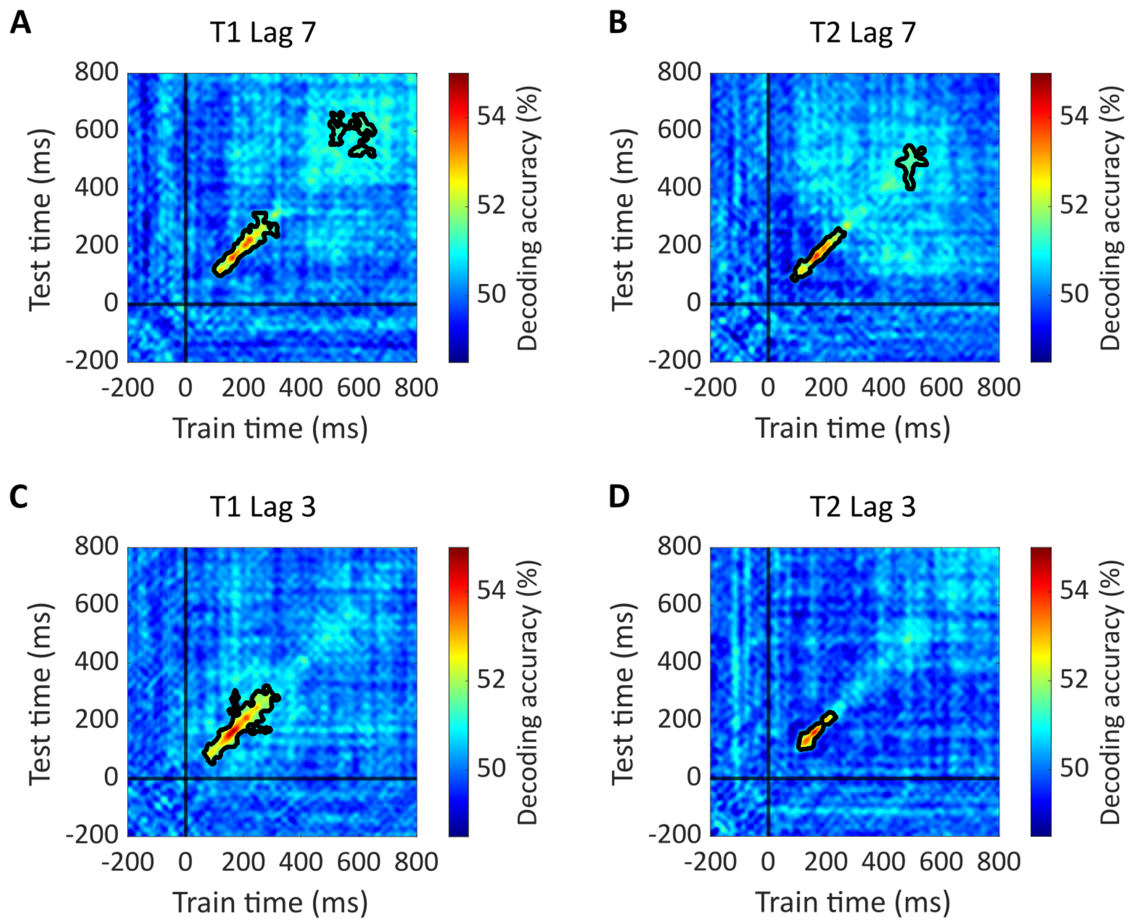

Figure 3.2: Temporal generalization maps. Temporal generalization maps for T1 **(A)** and T2 **(B)** in lag 7 condition. Initially, a slender diagonal pattern emerged, which later transformed into a wider square-shaped pattern. Temporal generalization maps for T1 **(C)** and T2 **(D)** in lag 3. Only narrow diagonal patterns emerged early in time. Warmer colors indicate higher decoding accuracy. Black vertical and horizontal lines show the corresponding target onset. Significant clusters, shown with a black contour were calculated using one-sided permutation tests and corrected with cluster correction (N=32 participants; cluster defining threshold $p < 0.01$, corrected significance level $p < 0.05$, 10000 permutations).

3.4 Early target representations are not affected by T2 identification

To calculate the decoding accuracy time series for T2, we used all T2 trials regardless of correct or incorrect responses. This raises the question of how the neural representations differ between correct and incorrect T2 responses. To answer this question, we separated the trials based on whether T2 was reported correctly and then calculated the decoding accuracy time series for correct versus incorrect T2 responses in lag 3 condition, the AB condition. We observed that decoding accuracy was at chance level until 400 ms after T2 onset indicating that the early processing of correct and incorrect responses were similar (Meijs et al., 2019; Alilović et al., 2021). However, the decoding accuracy of correct versus incorrect responses rose significantly from around 500 ms to 800 ms, showing that late stages of processing differed between correct and incorrect T2 responses (Figure 3.3 A).

3.5 Blinkers and non-blinkers exhibit different target representations

Finally, we aimed to investigate the individual differences in our attentional blink paradigm. It has been previously shown that the performance of individuals in an AB task varies to the extent that some individuals show no AB at all (Willems and Martens, 2016). Consequently, we can categorize the participants into two distinct groups: ”blinkers” who demonstrate AB effect in their behavior performance, and ”non-blinkers” who show small or no AB effect in their behavior performance.

According to previous studies, attentional blink is defined as a significant change in T2 performance when the two targets are presented in close temporal succession. Thus, we separated participants into two groups based on the difference in target identification accuracy between lag 7 and lag 3 (Colzato et al., 2007; Arnell et al., 2010). We set a threshold for this difference, if the accuracy difference was higher than 3% then the participant was a blinker; otherwise, the participant was a non-blinker. The average accuracy difference was higher in blinkers compared to non-blinkers (Blinkers: N=19 participants, mean=8.85%, SE=0.99%; Non-blinkers: N=13 participants, mean=-0.22%, SE=0.95%). We separately calculated the decoding accuracy time series of T1 and T2 for blinkers and non-blinkers in lag 3 and lag 7 conditions (Figure 3.3 B-E).

We observed that the magnitude of the first rise in the decoding accuracy of both T1 and T2 was higher in non-blinkers in comparison to blinkers, especially in lag 3 condition (AB condition). Since the number of participants in the blinker and the non-blinker groups were few and different, we could not compare blinkers and non-blinkers decoding accuracy time series quantitatively, but this finding might indicate that target images were discriminated better in non-blinkers' brains. Moreover, in the lag 3 condition (Figure 3.3 D), after the early rise in the decoding accuracy of T1, a significant interval in the decoding accuracy of non-blinkers can be seen around 400 to 600 ms after the target onset, but there was no such rise in decoding accuracy of the blinkers.

Comparing the decoding accuracy of blinkers and non-blinkers in lag 3, we first found that non-blinkers decoding accuracy magnitude was higher than blinkers during the early rise of the decoding accuracy. This might indicate that non-blinkers were better at target discrimination. Second, the late significant interval in non-blinkers decoding accuracy time series for T1 in lag 3 condition revealed that the interference between T2 and T1 in non-blinkers was less pronounced during attentional blink compared to blinkers. These findings may suggest that non-blinkers are able to process targets more efficiently.

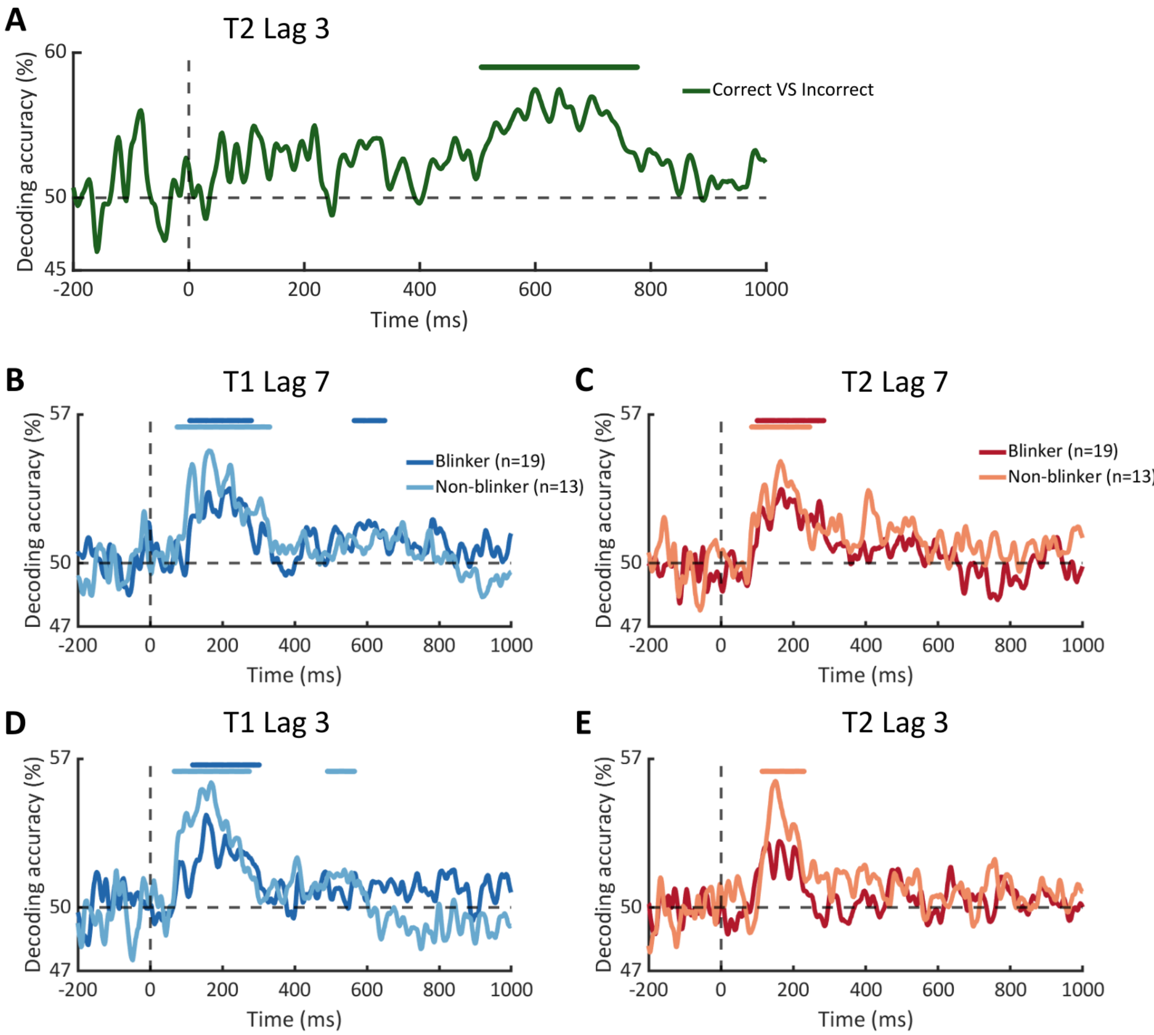

Figure 3.3: Decoding analysis for T2 responses and blinkers and non-blinkers. **(A)** Decoding accuracy time series for correct versus incorrect T2 responses in lag 3 condition (N=32). Decoding accuracy time series of T1 in lag 7 **(B)** and lag 3 **(D)** for blinkers and non-blinkers. Dark blue graphs indicate the blinker group (N=19 participants) and light blue color shows the non-blinker group (N=13 participants). Decoding accuracy time series of T2 in lag 7 **(C)** and lag 3 **(E)** for blinkers and non-blinkers. The dark red color indicates the blinker group and the light red color shows the non-blinker group. The vertical dashed lines show the corresponding target onset. The horizontal dashed lines show a 50% chance level. The lines above the graphs are significant intervals that were calculated using one-sided permutation tests and corrected with cluster correction (cluster defining threshold $p < 0.05$, corrected significance level $p < 0.05$, 10000 permutations).

3.6 Results summary

First, we found a significant effect of lag in T2 identification accuracy (attentional blink) and T1 identification accuracy indicating that both T1 and T2 processings were affected by lag conditions. Second, we compared the neural representations of targets in lag 3 and lag 7, and we found that T1 and T2 processings interfered with each other in lag 3 but not lag 7 which can explain why attentional blink occurs in short lag conditions. We then confirmed this finding by analyzing the temporal generalization maps of target processing. This analysis confirmed the suppressed processing of targets in lag 3 while revealing sustained processing of later stages in lag 7. Furthermore, we found that the early processing of targets was intact during the attentional blink; however, the later processing was suppressed. We observed the same pattern comparing correct and incorrect T2 responses. The first stages of processing were similar in correct versus incorrect T2 decoding accuracy; however, the later stages could be discriminated by decoding analysis. Third, we compared blinkers and non-blinkers target representations and observed that the early rise in decoding accuracy was stronger in non-blinkers. Moreover, T1 and T2 processing coincided less with each other in lag 3 in non-blinkers which may explain why non-blinkers show no or small AB effect.

Chapter 4

Discussion

The present study aimed to contrast the neural dynamics associated with target processing under conditions where attentional blink does or does not occur. We used an attentional blink paradigm with two face targets and two lag (inter-target interval) conditions: a short lag condition expected to induce the attentional blink, and a long lag condition, where the attentional blink is expected not to happen. We collected EEG and behavioral data from participants as they engaged in a task involving the identification of two face target images within a rapid stream of natural object distractors. Using multivariate pattern analysis of EEG data we calculated the neural representations of target processing over time under the two lag conditions.

4.1 Target identification accuracy depends on lag

At the behavioral level, we observed a significant impairment in the second target identification accuracy in lag 3 confirming the attentional blink phenomenon. Intriguingly, we also observed a similar pattern of decline in the identification accuracy of the first target. This finding indicated that the first target processing might be influenced by the time interval between targets. Previously, T1 identification accuracy has been used as a baseline for T2 identification accuracy to determine whether AB occurred in a study (Chua, 2005; McLaughlin et al., 2001). However, according to MacLean and Arnell, 2012, the use of T1 identification accuracy as a baseline in studies where the identifying tasks for T1 and T2 differ is not appropriate. Additionally, based on our results, even when the identifying tasks for both targets are the same, the T1 identification accuracy may vary across different lags. Therefore, the traditional practice of using T1 identification accuracy as a baseline to evaluate attentional blink may not be applicable in all experiments. Furthermore, our findings emphasize the importance of exercising caution when generalizing previous findings from basic stimuli to make predictions regarding visual performance under more naturalistic conditions (Einhäuser et al., 2007).

4.2 MVPA of EEG data uncovered the impact of lag on target representations.

We presented a series of multivariate pattern analyses, in which we first found that the identity of individual faces can be decoded reliably using EEG data. It is important to note that the target stimulus set we used shared several features such as grayscale color and facial expression; therefore, the maximum decoding accuracy magnitude was relatively low (~ %56). Moreover, comparing target representations across lag 7 and lag 3, we found that the early processing of both T1 and T2 was highly similar in the two lag conditions. This might suggest that attentional blink does not affect the early processing of targets. However, we observed a chance level decoding accuracy after 300 ms of the target onset in lag 3, indicating that the later processing of targets was suppressed in lag 3, where attentional blink occurs, but not in lag 7. In lag 7, on the other hand, where there was an additional time between the two targets, another significant rise (later processing stages) could be seen in the decoding accuracy of targets around 400 to 600 ms after the target onset. The similar pattern of T1 and T2 decoding accuracy in lag 3 and lag 7 suggests that both T1 and T2 processing were inhibited when they emerged closely one after the other.

Our results are in opposition to the limited-capacity theory, which suggests that our attention system's resources become occupied with processing the first target during a rapid presentation of images; as a result, there are insufficient resources for processing the second target, which causes the attentional blink (Dux and Marois, 2009). In certain models within this category, it has been proposed that T2 processing should be delayed until T1 processing is completed. However, in situations where there is limited time between stimuli (short lag conditions), T1 processing may not have sufficient time to finish before the arrival of T2; as a result, T2 cannot be adequately processed, leading to attentional blink (Chun and Potter, 1995; Marti et al., 2012). In our results; however, the early stages of target processing can be seen for both targets in the lag 3 condition. Furthermore, both targets' late processing was restricted which suggests that the available resources are engaged with both targets simultaneously rather than completing the first target processing before starting the second target processing.

Moreover, we confirmed the suppression of target representations beyond 300 ms of target onset (later stages of processing) by evaluating the temporal generalization results. The temporal generalization maps showed a narrow diagonal pattern around 100 to 300 ms after the target onset indicating that the target representations evolve transiently in the first stages of processing. Later in time, there was a broad square-shaped pattern in the temporal generalization of targets in the lag 7 condition, suggesting the involvement of higher-level processes in target identification. In contrast, such patterns cannot be seen in the lag 3 condition, indicating that the high-level processes are suppressed during the attentional blink condition. Similar to decoding analysis results, these findings imply that both T1 and T2 representations are more sustained when there is enough time between the targets (lag 7) which is contrary to the limited capacity models of the attentional blink. Previous studies also suggested a similar pattern in the temporal generalization maps of T2, when T2 was a letter or digit image (Meijs et al., 2019; Alilović et al., 2021). Decoding analysis and temporal generalization analysis are in line with behavioral results, showing the impairment of T1 and T2 identification accuracy in the lag 3 condition compared to the lag 7 condition.

In the next step, we investigated the difference between neural representations of correct and incorrect responses of the second target. To do so, we divided the trials into two groups and labeled them based on the correct or incorrect T2 responses. Subsequently, we calculated the decoding accuracy of correct versus incorrect responses. We observed no significant difference between correct and incorrect T2 responses at early times indicating that early processing of the target is intact regardless of correct identification of target (Meijs et al., 2019; Alilović et al., 2021). Nonetheless, a significant difference can be seen later in time from ~500 to ~800 ms, meaning that the late stages of processing were different when participants correctly identified the second target.

Taking these results into account, we observed two stages of processing in the neural representations of face targets in an attentional blink paradigm with natural stimuli. This is aligned with previous studies that used an attentional blink paradigm with basic stimuli (such as digits, letters, or objects without background) (Kaiser et al., 2016; Alilović et al., 2021; Meijs et al., 2019). The early stage, which appeared as a significant rise in the decoding accuracy of the targets, started as early as 100 ms and continued until 300 ms after the target onset. This early processing was not significantly different for T1 and T2 in lag 3 and lag 7 conditions, meaning that the early target processing was not affected by attentional blink. One possible implication could be that the early stages of target processing are processed unconsciously; thus, regardless of the lag condition or target location in a rapid series, early processing occurs similarly. In our findings, the early stage was even similar between correct and incorrect T2 responses, confirming that the immediate processes following the target onset occur unconsciously. The second stage of processing can be seen around 400 to 600 ms after the target onset only in lag 7 condition, showing that this stage of processing is affected by attentional blink. Therefore, the late stages of processing might be associated with the conscious identification of the target. Additionally, we observed that this late pattern in the neural representations of the target was similar for both T1 and T2, indicating that the late stages of both targets' processing in an attentional blink paradigm depend on the time interval between the two targets.

Our findings contradict the limited-capacity theories, which propose that the attentional blink results from the constrained capacity or resources in the working memory (Jolicœur and

Dell'Acqua, 1998; Potter et al., 2002; Dehaene et al., 2003). Instead, our findings are more in line with attentional control theories (Nieuwenstein et al., 2005; Olivers and Meeter, 2008; Olivers et al., 2007). These theories posit that the attentional blink transpires due to the interference of targets and distractors' attentional sets. Attentional control theories provide the explanation of why T1 representations, just as T2 representations, were suppressed in the lag 3 condition. Although our results do not directly investigate the impact of distractors on the neural representations of targets, it would be interesting for future studies to explore and compare the neural representations of both distractors and targets, as well as their potential interactions.

4.3 Target representations are different between blinkers and non-blinkers.

We aimed to examine the individual differences in our study; thus, we divided our participants into two groups: blinkers, who show a strong AB effect, and non-blinkers, who show a small AB effect in their behavior results. Previous studies examined individual differences in attentional blink using ERP analysis of EEG data (Martens et al., 2006; Troche and Rammsayer, 2013). Martens et al., 2006 found a delayed P3 component in ERPs of blinkers, and they suggested that non-blinkers have a faster ability to consolidate the identity of targets. Furthermore, Troche and Rammsayer, 2013 showed that the P3 component is suppressed during attentional blink.

We found that non-blinkers neural representations were stronger in the early stages of processing which may explain why non-blinkers are better at distinguishing targets. Moreover, we observed a significant peak in the decoding accuracy of T1 in the lag 3 condition in non-blinkers. This means that the first target was further processed in non-blinker groups and the interference between the two targets was less observed. It is important to note that the number of participants in the two groups of blinkers and non-blinkers was not identical and the sample size was small; therefore, we could not compare them quantitatively. However, it would be an interesting complementary study to contrast blinkers and non-blinker neural representations with a higher sample size to find out why the effect varies among participants.

4.4 Conclusion

In conclusion, first, we demonstrated that the neural representation of face targets in a rapid serial visual presentation of natural object images can be decoded from neural activity measured by EEG. Second, we showed that the late neural representations of targets are suppressed if the second target is presented within 200 - 500 ms of the first target, the attentional blink period; thus, both the first and the second target identification accuracy is reduced. On the other hand, the early representations of targets are similar regardless of the targets' lag and/or the behavioral performance of participants. Third, we observed that the neural representations of face processing might be stronger in non-blinker participants than in blinkers. Our findings contradict early theories of the attentional blink, such as limited capacity theories. Instead, our results are more in line with attentional control theories. However, further research is needed to fully determine the extent to which our findings support attentional control theories.

4.5 Limitation

While this study has provided valuable insights into understanding the attentional blink phenomenon, it is important to acknowledge several limitations that could have influenced the outcomes.

To begin with, we examined the targets decoding accuracy time series in lag 7 and lag 3, comparing them against chance levels, and identifying statistically significant time points. Nevertheless, a direct contrast between decoding accuracy at lag 7 and lag 3 was challenging due to the minimal effect size, as the difference in decoding accuracy magnitude between lag 3 and lag 7 was very small. A direct comparison between the decoding accuracy time series in the two lag conditions can enhance the robustness of our finding. Secondly, another limitation was encountered in the separate analysis of correct and incorrect T2 responses. The presence of a few incorrect trials, particularly within the lag 7 condition, limited our ability to investigate the decoding accuracy time series for correct and incorrect T2 responses separately within each lag condition. Instead, we compared all correct responses to all incorrect T2 responses in lag 3 condition (See Methods section 2.9).

Furthermore, in examining individual differences, we categorized participants into two groups (blinkers and non-blinkers) resulted in relatively small sample sizes for each group. This limited the statistical power of decoding analysis for blinkers and non-blinkers; as a result, we have not compared them statistically, but a robust comparison might be achieved with a larger sample size. Lastly, there was a limitation in our approach to participant inclusion. Prior to the multivariate pattern analysis, we removed all trials with T1 incorrect responses; thus, we excluded participants who exhibited less than 50% T1 reporting accuracy. While this decision was made to ensure data quality, it led to the exclusion of a subset of participants (3 out of 35).

Addressing these limitations in future research endeavors could potentially yield more comprehensive results and advance our understanding of this area of research.

References

Josipa Alilović, Dirk van Moorselaar, Marcel Graetz, Simon van Gaal, and Heleen A. Slagter. Representational dynamics preceding conscious access. *NeuroImage*, 230:117789, April 2021. ISSN 1053-8119. doi: 10.1016/j.neuroimage.2021.117789.

Isabel Arend, Stephen Johnston, and Kimron Shapiro. Task-irrelevant visual motion and flicker attenuate the attentional blink. *Psychonomic Bulletin & Review*, 13(4):600–607, August 2006. ISSN 1069-9384. doi: 10.3758/bf03193969.

Karen M. Arnell, Kirk A. Stokes, Mary H. MacLean, and Carleen Gicante. Executive control processes of working memory predict attentional blink magnitude over and above storage capacity. *Psychological Research*, 74(1):1–11, January 2010. ISSN 1430-2772. doi: 10.1007/s00426-008-0200-4.

Laura Batterink, Christina M. Karns, and Helen Neville. Dissociable Mechanisms Supporting Awareness: The P300 and Gamma in a Linguistic Attentional Blink Task. *Cerebral Cortex*, 22(12):2733–2744, December 2012. ISSN 1047-3211. doi: 10.1093/cercor/bhr346.

D. H. Blackwood and W. J. Muir. Cognitive brain potentials and their application. *The British Journal of Psychiatry. Supplement*, (9):96–101, 1990. ISSN 0960-5371.

Donald E. Broadbent and Margaret H. P. Broadbent. From detection to identification: Response to multiple targets in rapid serial visual presentation. *Perception & Psychophysics*, 42(2): 105–113, March 1987. ISSN 1532-5962. doi: 10.3758/BF03210498.

Marisa Carrasco. Visual attention: The past 25 years. *Vision Research*, 51(13):1484–1525, July 2011. ISSN 0042-6989. doi: 10.1016/j.visres.2011.04.012.

Chih-Chung Chang and Chih-Jen Lin. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2(3):27:1–27:27, May 2011. ISSN 2157-6904. doi: 10.1145/1961189.1961199.

Fook K. Chua. The effect of target contrast on the attentional blink. *Perception & Psychophysics*, 67(5):770–788, July 2005. ISSN 1532-5962. doi: 10.3758/BF03193532.

Marvin Chun and Mary Potter. A Two-Stage Model for Multiple Target Detection in Rapid Serial Visual Presentation. *Journal of experimental psychology. Human perception and performance*, 21:109–27, March 1995. doi: 10.1037/0096-1523.21.1.109.

Lorenza S. Colzato, Michiel M. A. Spapé, Merel M. Pannebakker, and Bernhard Hommel. Working memory and the attentional blink: Blink size is predicted by individual differences in operation span. *Psychonomic Bulletin & Review*, 14(6):1051–1057, December 2007. ISSN 1531-5320. doi: 10.3758/BF03193090.

Stanislas Dehaene, Claire Sergent, and Jean-Pierre Changeux. A neuronal network model linking subjective reports and objective physiological data during conscious perception. *Proceedings of the National Academy of Sciences*, 100(14):8520–8525, July 2003. doi: 10.1073/pnas.1332574100. Publisher: Proceedings of the National Academy of Sciences.

R. Dell'acqua, P. Jolicoeur, F. Pesciarelli, R. Job, and D. Palomba. Electrophysiological evidence of visual encoding deficits in a cross-modal attentional blink paradigm. *Psychophysiology*, 40(4):629–639, 2003. ISSN 1469-8986. doi: 10.1111/1469-8986.00064.

Vincent Di Lollo, Jun-ichiro Kawahara, S.M. Shahab Ghorashi, and James T. Enns. The attentional blink: Resource depletion or temporary loss of control? *Psychological Research*, 69 (3):191–200, January 2005. ISSN 1430-2772. doi: 10.1007/s00426-004-0173-x.

Paul E. Dux and René Marois. The attentional blink: A review of data and theory. *Attention, Perception, & Psychophysics*, 71(8):1683–1700, November 2009. ISSN 1943-393X. doi: 10.3758/APP.71.8.1683.

Wolfgang Einhäuser, Christof Koch, and Scott Makeig. The duration of the attentional blink in natural scenes depends on stimulus category. *Vision Research*, 47(5):597–607, March 2007. ISSN 0042-6989. doi: 10.1016/j.visres.2006.12.007.

Tijl Grootswagers, Susan G. Wardle, and Thomas A. Carlson. Decoding Dynamic Brain Patterns from Evoked Responses: A Tutorial on Multivariate Pattern Analysis Applied to Time Series Neuroimaging Data. *Journal of Cognitive Neuroscience*, 29(4):677–697, April 2017. ISSN 1530-8898. doi: 10.1162/jocn_a_01068.

Martin N. Hebart, Adam H. Dickter, Alexis Kidder, Wan Y. Kwok, Anna Corriveau, Caitlin Van Wicklin, and Chris I. Baker. THINGS: A database of 1,854 object concepts and more than 26,000 naturalistic object images. *PLOS ONE*, 14(10):e0223792, October 2019. ISSN 1932-6203. doi: 10.1371/journal.pone.0223792. Publisher: Public Library of Science.

James E. Hoffman, Billie Nelson, and Michael R. Houck. The role of attentional resources in automatic detection. *Cognitive Psychology*, 15(3):379–410, July 1983. ISSN 0010-0285. doi: 10.1016/0010-0285(83)90013-0.

Pierre Jolicœur and Roberto Dell'Acqua. The Demonstration of Short-Term Consolidation. *Cognitive Psychology*, 36(2):138–202, July 1998. ISSN 0010-0285. doi: 10.1006/cogp.1998.0684.

Daniel Kaiser, Damiano C. Azzalini, and Marius V. Peelen. Shape-independent object category responses revealed by MEG and fMRI decoding. *Journal of Neurophysiology*, 115(4):2246–2250, April 2016. ISSN 1522-1598. doi: 10.1152/jn.01074.2015.

Tero Karras, Samuli Laine, and Timo Aila. A Style-Based Generator Architecture for Generative Adversarial Networks, March 2019. arXiv:1812.04948 [cs, stat].

J.-R. King and S. Dehaene. Characterizing the dynamics of mental representations: the temporal generalization method. *Trends in Cognitive Sciences*, 18(4):203–210, April 2014. ISSN 1879-307X. doi: 10.1016/j.tics.2014.01.002.

Mario Kleiner, David Brainard, and Denis Pelli. What's new in Psychtoolbox-3? 2007. Publisher: Pion Ltd.

Cornelia Kranczioch, Stefan Debener, and Andreas K. Engel. Event-related potential correlates of the attentional blink phenomenon. *Brain Research. Cognitive Brain Research*, 17(1):177–187, June 2003. ISSN 0926-6410. doi: 10.1016/s0926-6410(03)00092-2.

Mary H. MacLean and Karen M. Arnell. A conceptual and methodological framework for measuring and modulating the attentional blink. *Attention, Perception, & Psychophysics*, 74 (6):1080–1097, August 2012. ISSN 1943-393X. doi: 10.3758/s13414-012-0338-4.

Scott Makeig, Anthony Bell, Tzyy-Ping Jung, and Terrence Sejnowski. Independent Component Analysis of Electroencephalographic Data. 8, August 1996.

Eric Maris and Robert Oostenveld. Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods*, 164(1):177–190, August 2007. ISSN 0165-0270. doi: 10.1016/j.jneumeth.2007.03.024.

Sander Martens and Brad Wyble. The attentional blink: past, present, and future of a blind spot in perceptual awareness. *Neuroscience and Biobehavioral Reviews*, 34(6):947–957, May 2010. ISSN 1873-7528. doi: 10.1016/j.neubiorev.2009.12.005.

Sander Martens, Jaap Munneke, Hendrikus Smid, and Addie Johnson. Quick Minds Don't Blink: Electrophysiological Correlates of Individual Differences in Attentional Selection. *Journal of Cognitive Neuroscience*, 18(9):1423–1438, September 2006. ISSN 0898-929X. doi: 10.1162/jocn.2006.18.9.1423.

Sébastien Marti, Mariano Sigman, and Stanislas Dehaene. A shared cortical bottleneck underlying Attentional Blink and Psychological Refractory Period. *NeuroImage*, 59(3):2883–2898, February 2012. ISSN 1095-9572. doi: 10.1016/j.neuroimage.2011.09.063.

Elizabeth N. McLaughlin, David I. Shore, and Raymond M. Klein. The Attentional Blink is Immune to Masking-Induced Data Limits. *The Quarterly Journal of Experimental Psychology Section A*, 54(1):169–196, February 2001. ISSN 0272-4987. doi: 10.1080/02724980042000075. Publisher: SAGE Publications.

Erik L Meijs, Pim Mostert, Heleen A Slagter, Floris P de Lange, and Simon van Gaal. Exploring the role of expectations and stimulus relevance on stimulus-specific neural representations and conscious report. *Neuroscience of Consciousness*, 2019(1):niz011, January 2019. ISSN 2057-2107. doi: 10.1093/nc/niz011.

Yalda Mohsenzadeh, Sheng Qin, Radoslaw M Cichy, and Dimitrios Pantazis. Ultra-Rapid serial visual presentation reveals dynamics of feedforward and feedback processes in the ventral visual pathway. *eLife*, 7:e36329, June 2018. ISSN 2050-084X. doi: 10.7554/eLife.36329. Publisher: eLife Sciences Publications, Ltd.

Mark R. Nieuwenstein, Marvin M. Chun, Rob H. J. van der Lubbe, and Ignace T. C. Hooge. Delayed attentional engagement in the attentional blink. *Journal of Experimental Psychology. Human Perception and Performance*, 31(6):1463–1475, December 2005. ISSN 0096-1523. doi: 10.1037/0096-1523.31.6.1463.

Christian N. L. Olivers and Martijn Meeter. A boost and bounce theory of temporal attention. *Psychological Review*, 115(4):836–863, October 2008. ISSN 0033-295X. doi: 10.1037/a0013395.

Christian N. L. Olivers and Sander Nieuwenhuis. The beneficial effects of additional task load, positive affect, and instruction on the attentional blink. *Journal of Experimental Psychology.*

Human Perception and Performance, 32(2):364–379, April 2006. ISSN 0096-1523. doi: 10.1037/0096-1523.32.2.364.

Christian N. L. Olivers, Stefan van der Stigchel, and Johan Hulleman. Spreading the sparing: against a limited-capacity account of the attentional blink. *Psychological Research*, 71(2): 126–139, March 2007. ISSN 1430-2772. doi: 10.1007/s00426-005-0029-z.

Denis G. Pelli and Spatial Vision. The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial vision*, 10:437–442, 1997. Publisher: VSP.

Vincent Jetté Pomerleau, Ulysse Fortier-Gauthier, Isabelle Corriveau, Roberto Dell'Acqua, and Pierre Jolicœur. Colour-specific differences in attentional deployment for equiluminant pop-out colours: Evidence from lateralised potentials. *International Journal of Psychophysiology*, 91(3):194–205, March 2014. ISSN 0167-8760. doi: 10.1016/j.ijpsycho.2013.10.016.

Mary C. Potter, Adrian Staub, Janina Rado, and Daniel H. O'Connor. Recognition memory for briefly presented pictures: The time course of rapid forgetting. *Journal of Experimental Psychology: Human Perception and Performance*, 28(5):1163–1175, 2002. ISSN 1939-1277. doi: 10.1037/0096-1523.28.5.1163. Place: US Publisher: American Psychological Association.

Mary C. Potter, Brad Wyble, Carl Erick Hagmann, and Emily S. McCourt. Detecting meaning in RSVP at 13 ms per picture. *Attention, Perception, & Psychophysics*, 76(2):270–279, February 2014. ISSN 1943-393X. doi: 10.3758/s13414-013-0605-z.

Jane E. Raymond, Kimron L. Shapiro, and Karen M. Arnell. Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of Experimental Psychology: Human Perception and Performance*, 18(3):849–860, 1992. ISSN 1939-1277. doi: 10.1037/0096-1523.18.3.849. Place: US Publisher: American Psychological Association.

Walter Schneider and Richard M. Shiffrin. Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, 84(1):1–66, 1977. ISSN

1939-1471. doi: 10.1037/0033-295X.84.1.1. Place: US Publisher: American Psychological Association.

P. Sessa, R. Luria, R. Verleger, and R. Dell'Acqua. P3 latency shifts in the attentional blink: Further evidence for second target processing postponement. *Brain Research*, 1137:131–139, March 2007. ISSN 0006-8993. doi: 10.1016/j.brainres.2006.12.066.

Shravani Sur and V. K. Sinha. Event-related potential: An overview. *Industrial Psychiatry Journal*, 18(1):70–73, 2009. ISSN 0972-6748. doi: 10.4103/0972-6748.57865.

François Tadel, Sylvain Baillet, John C. Mosher, Dimitrios Pantazis, and Richard M. Leahy. Brainstorm: a user-friendly application for MEG/EEG analysis. *Computational Intelligence and Neuroscience*, 2011:879716, 2011. ISSN 1687-5273. doi: 10.1155/2011/879716.

Matthew F. Tang, Lucy Ford, Ehsan Arabzadeh, James T. Enns, Troy A. W. Visser, and Jason B. Mattingley. Neural dynamics of the attentional blink revealed by encoding orientation selectivity during rapid visual presentation. *Nature Communications*, 11(1):434, January 2020. ISSN 2041-1723. doi: 10.1038/s41467-019-14107-z. Number: 1 Publisher: Nature Publishing Group.

Anne M. Treisman and Garry Gelade. A feature-integration theory of attention. *Cognitive Psychology*, 12(1):97–136, January 1980. ISSN 0010-0285. doi: 10.1016/0010-0285(80)90005-5.

Stefan J. Troche and Thomas H. Rammsayer. Attentional blink and impulsiveness: evidence for higher functional impulsivity in non-blinkers compared to blinkers. *Cognitive Processing*, 14(3):273–281, August 2013. ISSN 1612-4790. doi: 10.1007/s10339-013-0553-5.

Rolf Verleger, Andreas Sprenger, Sina Gebauer, Michaela Fritzmannova, Monique Friedrich, Stefanie Kraft, and Piotr Jaśkowski. On Why Left Events are the Right Ones: Neural Mechanisms Underlying the Left-hemifield Advantage in Rapid Serial Visual Presentation.

Journal of Cognitive Neuroscience, 21(3):474–488, March 2009. ISSN 0898-929X. doi: 10.1162/jocn.2009.21038.

E. K. Vogel, S. J. Luck, and K. L. Shapiro. Electrophysiological evidence for a postperceptual locus of suppression during the attentional blink. *Journal of Experimental Psychology. Human Perception and Performance*, 24(6):1656–1674, December 1998. ISSN 0096-1523. doi: 10.1037//0096-1523.24.6.1656.

Edward K. Vogel and Steven J. Luck. Delayed working memory consolidation during the attentional blink. *Psychonomic Bulletin & Review*, 9(4):739–743, December 2002. ISSN 1531-5320. doi: 10.3758/BF03196329.

Charlotte Willems and Sander Martens. Time to see the bigger picture: Individual differences in the attentional blink. *Psychonomic Bulletin & Review*, 23(5):1289–1299, October 2016. ISSN 1531-5320. doi: 10.3758/s13423-015-0977-2.

Verena Willenbockel, Javid Sadr, Daniel Fiset, Greg O. Horne, Frédéric Gosselin, and James W. Tanaka. Controlling low-level image properties: the SHINE toolbox. *Behavior Research Methods*, 42(3):671–684, August 2010. ISSN 1554-3528. doi: 10.3758/BRM.42.3.671.

Fangshu Yao and Bin Zhou. It's time for attentional control: Temporal expectation in the attentional blink. *Consciousness and Cognition*, 107:103461, January 2023. ISSN 1053-8100. doi: 10.1016/j.concog.2022.103461.

Alon Zivony and Dominique Lamy. What processes are disrupted during the attentional blink? An integrative review of event-related potential research. *Psychonomic Bulletin & Review*, 29(2):394–414, April 2022. ISSN 1531-5320. doi: 10.3758/s13423-021-01973-2.

Appendix A

Results Appendix

To see the differences between correct and incorrect T2 responses, a better approach, instead of the method we used in section 2.9, is to examine the decoding accuracy time series of T2 correct and incorrect responses separately (See Discussion section 4.5).

To compare correct and incorrect T2 responses separately in the lag 3 condition, we added correct or incorrect labels to the trials in T2 and lag 3 condition based on whether T2 was identified correctly. We followed the same process described in the Methods, decoding analysis section 2.6 to calculate the decoding accuracy time series for correct and incorrect T2 responses in lag 3 conditions. Since the number of correct and incorrect trials varied across labels we bootstrapped the trials before sub-averaging to make sure the signal-to-noise ratio is similar for all input folds. The decoding accuracy time series for correct and incorrect T2 responses in the lag 3 condition were calculated by averaging pairwise classification accuracies across correct labels and incorrect labels respectively.

The decoding accuracy time series for correct and incorrect T2 responses are shown in Figure A.1. We observed a similar early rise in the decoding accuracy of the correct and incorrect responses, indicating that early processing was almost intact during the attentional blink (Meijs et al., 2019; Alilović et al., 2021). However, the early rise was weaker in incorrect responses. This might be because of the few number of incorrect trials in decoding analysis or it might indicate that the early processing was slightly suppressed when participants did not identify the target correctly. Furthermore, a late rise in decoding accuracy can be seen for correct responses but not for incorrect responses, showing that the processing of T2 was continued when participants identified the target correctly. However, T2 was not further processed when participants did not identify it.

Taking the findings into account, we observed that the early processing in correct and incorrect T2 responses did not differ much; however, the later processing can be only seen in correct responses decoding accuracy time series (Meijs et al., 2019; Alilović et al., 2021). It is important to reiterate that there were a few incorrect T2 responses; consequently, the classifier had limited training samples, resulting in a considerable amount of noise in the obtained results. Due to this limitation, we were unable to make a comprehensive comparison between correct and incorrect T2 responses decoding accuracy time series using this method. As a result, it is recommended that future studies use more repetitions per target image if they aim to compare correct and incorrect neural representations of the target.

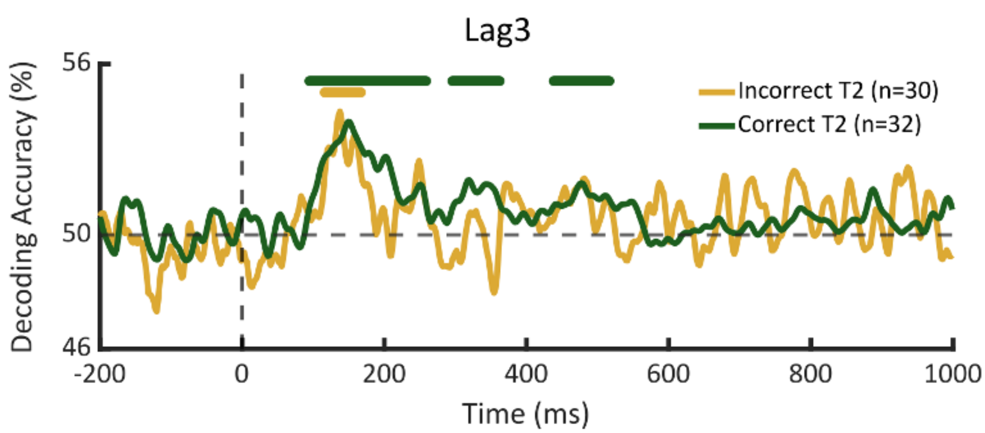

Figure A.1: Decoding accuracy time series for correct (green) and incorrect (yellow) T2 responses in lag 3. The vertical dashed line shows the T2 onset. The horizontal dashed line shows a 50% chance level. The lines above the graphs are significant intervals that were calculated using one-sided permutation tests and corrected with cluster correction (cluster defining threshold $p < 0.05$, corrected significance level $p < 0.05$, 10000 permutations).

Appendix B

Ethics Approval

Figure B.1 Shows the ethics letter approved by Health Science Research Ethics Board (HSREB). The application was submitted through Western Research Ethics Manager (WREM).

Western Research

Date: 18 July 2022

To: Dr Yalda Mohsenzadeh

Project ID: 120820

Review Reference: 2022-120820-68734

Study Title: Neural Dynamics of Perception in Rapid Serial Visual Presentation

Application Type: HSREB Initial Application

Review Type: Delegated

Full Board Reporting Date: 09/Aug/2022

Date Approval Issued: 18/Jul/2022 06:56

REB Approval Expiry Date: 18/Jul/2023

Dear Dr Yalda Mohsenzadeh

The Western University Health Science Research Ethics Board (HSREB) has reviewed and approved the above mentioned study as described in the WREM application form, as of the HSREB Initial Approval Date noted above. This research study is to be conducted by the investigator noted above. **All other required institutional approvals and mandated training must also be obtained prior to the conduct of the study**.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
VisualStimuli	Other Data Collection Instruments		
Poster	Recruitment Materials	09/Jun/2022	
Email	Email Script	09/Jun/2022	
MRI_PatientScreeningForm	Other Data Collection Instruments	09/Jun/2022	
Email_behavioral	Email Script	06/Jul/2022	
Protocol_behavior	Protocol	06/Jul/2022	
Poster_behavioral	Recruitment Materials	06/Jul/2022	
Letter of information_behavioral	Written Consent/Assent	06/Jul/2022	
Protocol	Protocol	09/Jun/2022	

No deviations from, or changes to, the protocol or WREM application should be initiated without prior written approval of an appropriate amendment from Western HSREB , except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University HSREB operates in compliance with, and is constituted in accordance with, the requirements of the TriCouncil Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the International Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Products Regulations; Part 3 of the Medical Devices Regulations and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000940.

Please do not hesitate to contact us if you have any questions.

Electronically signed by:

Ms. Nicola Geoghegan-Morphet , Ethics Officer on behalf of Dr. Philip Jones, HSREB Chair, 18/Jul/2022 06:56

Page 1 of 2

Figure B.1: Ethics approval letter.

Curriculum Vitae

Name:	Mansoure Jahanian
Post-Secondary Education and Degrees:	Western University London, Canada Sept 2021 - Aug 2023.
	Sharif University of Technology Tehran, Iran Sept 2016 - Feb 2021
Honours and Awards:	BrainsCAN Scholarship, Amount: 40,000$ Sept 2021 - Aug 2023
	Vector Research Grant, Amount: 4,000$ Sept 2022 - Aug 2023
	Ranked 30 among 200 thousand in Iranian University Entrance exam Aug 2016

Presentations:

Jahanian et al., Neural Dynamics of Target Processing in Attentional Blink, Organization for Human Brain Mapping Conference, July 2023, Montreal, Canada.

Jahanian et al., Neural Dynamics of Target Processing in Attentional Blink, Lake Ontario Visionary Establishment Conference, February 2023, Niagara Falls, Canada.