Neural underpinnings of preparatory processes:

The roles of prediction, previous experience and social context in attentional control

Dissertation

„kumulativ"

zur Erlangung des Grades eines

Doktor der Naturwissenschaften

(Dr. rer. nat.)

des Fachbereichs Psychologie der Philipps-Universität Marburg

Vorgelegt von

Herr Hossein Abbasi

aus Khomein, Iran

Marburg, September 2022

Vom Fachbereich Psychologie der Philipps-Universität Marburg (Hochschulkennziffer 1180) als Dissertation angenommen am

Erstgutachterin: Prof. Dr. Anna Schubö

Zweitgutachter: Prof. Dr. Dominik Endres

Tag der Disputation: 17.02.2023

Contents

SUMMARY

Every day we perform many tasks either individually or jointly with other people (*joint action*) which require us to deploy attention to the targets and suppress a set of distractors which otherwise impair our task performance. There are multiple factors which might boost the salience of the irrelevant objects, making it harder to suppress them, such as *selection history* (Awh, Belopolsky, & Theeuwes, 2012). On the other hand, task predictability facilitates target selection and distractor suppression via the proactive control mechanism (Braver, 2012) which engages before stimulus presentation. However, selection history influences have been shown to continue capturing attention even when participants can predict the upcoming task (Kadel, Feldmann-Wüstefeld, & Schubö, 2017). The other factors which influence the salience of an object, especially in joint action tasks, are social value and social context. Previous research has reported co-representation of the partner target by an agent (Sebanz, Knoblich, & Prinz, 2003), which is present in the cooperative context and absent in the competitive context (Hommel, Colzato, & van Den Wildenberg, 2009). There are, however, still some gaps in the literature that the present dissertation will cover. Firstly, it is not well-understood how proactive preparation is implemented in the presence of selection history. Importantly, knowledge about brain activation during task preparation and the influence of selection history on that is lacking. Secondly, the influence of the social value and social context on attentional capture and its neurophysiological mechanisms need more investigation, something that is going to be covered in the present dissertation.

The present dissertation is divided into two main parts. In the first part (Studies I – III), the core research question is whether and how task predictability modulates attentional biases induced by selection history. In the second part (Study IV), the core goal is to investigate the influence of social value and social context on attentional capture by the distractor. In the first part, to induce individual selection history, participants either categorize the color of the color singleton (color group) or the shape of the shape singleton (shape group) in a categorization task. Next, all participants perform a search task wherein a diamond-shape target has to be selected while a red circle is sometimes present. Crucially the tasks are combined with different levels of predictability (Studies I and II): In Study I the task sequence is either predictable or unpredictable, while it is always predictable in Study II, but with different degrees of reliability (high-predictable vs. low-predictable). These variations of task predictability allow for a systematic examination of the influence of proactive preparation on selection history attentional biases.

Study I demonstrated the engagement of proactive preparation when the upcoming task was predictable. This proactive preparation was reflected in reduced power of posterior pre-stimulus alpha-band, but only in predictable sequence blocks. Importantly, proactive preparation was scaled by individual selection history – the color group participants who needed more task-set reconfiguration when switching between the tasks benefitted more form task predictability and exerted stronger proactive preparation. Consequently, these participants didn’t need to exert strong stimulus-driven distractor suppression after stimulus onset. This was reflected in the amplitude of the early Pd component (a marker of early distractor suppression) which remained the same irrespective of task predictability. The shape group participants, however, had to compensate for their weaker proactive preparation before stimulus onset using an early suppression of the distractor as it was reflected in a larger early Pd amplitude in predictable than in unpredictable sequence blocks. The findings of Study I were extended in Study II wherein the task sequence was constant in a session and different between sessions. Increasing predictability was shown to have a small influence on proactive distractor suppression in the shape group, maybe because the knowledge about the target dimension was enough for optimal task performance and task predictability didn't change the dimensional information of the target and distractor for this group. However, participants in the color group exerted a stronger early distractor suppression when task predictability was more reliable, suggesting the utilization of proactive preparation when the task requires it.

Selection history increased attentional capture by the distractor's feature within the dimension involved in previous selections. This appeared as a distractor N2pc in the color group in Study II when the task predictability was less reliable. Proactive preparation facilitated suppression of the distractor by the color group participants as the distractor N2pc became smaller and the early Pd became larger when task predictability was more reliable. Although the color group participants had a larger benefit from task predictability, the target selection by these participants remained impaired when the color distractor was present. This impaired target selection was reflected in larger behavioral distractor costs (Studies I and II) and later onset of the target N2pc (Study I) in the color group than in the shape group. These findings demonstrate that proactive distractor suppression doesn't have the potency to negate attentional biases induced by selection history.

The impact of the selection history on the priority map was quantitatively evaluated using an algorithmic model in Study III. The model calculated the weight of four different maps such as history, color, shape, and orientation for each group. The color group showed a very prominent weight of the history map which was larger than that of the shape group. This quantified the more reliance of the color group participants on their selection history because they needed it to accomplish the categorization task. On the other hand, the weight of the shape map was the highest in the shape group. This suggests that the shape group participants could accomplish both tasks by relying on shape discrimination and without any need to refer to their history. Importantly, the color map had a larger weight in the color group than in the shape group, explaining the larger attentional capture by the distractor in the color group than in the shape group. In sum, the model could provide quantitative measures from each map, explaining how selection history interacts with physical salience in directing attention in the priority map.

In the second part of the present dissertation (Study IV), pairs of participants shared a joint task, either cooperatively or competitively, wherein participants had to respond to their own target (agent target vs. partner target). Crucially, a color distractor which was not the target for either of the participants (non-relevant distractor) was present in some trials. Although both the partner target and the non-relevant distractor were non-targets for the agent, they captured the agent's attention differently. While the partner target captured the agent's attention, as reflected in a negative lateralization of parieto-occipital alpha-band power and longer response time, the non-relevant distractor was suppressed and it was reflected in a positive lateralization of parieto-occipital alpha-band power. Importantly, attentional capture by the partner target depended on the social context. While the partner target captured the agent's attention in the cooperative condition, reflected in a negative lateralization of parieto-occipital alpha-band power, the same stimulus was suppressed in the competitive condition, as reflected in a positive lateralization of parieto-occipital alpha-band power. This indicated that participants tune their attention toward their partner target depending on the social context and the task.

In sum, the four studies completed in the present dissertation examined the influence of different factors such as previous experience, task predictability, social value and social context on attentional control. Previous experience with a feature dimension was shown to increase the salience of the stimuli in that dimension, thus increasing attentional capture. Although increasing task predictability was shown to decrease the attentional biases induced by selection history, it didn't negate the selection history influence entirely. Further, the social value was shown to change the salience of the stimuli. The partner target captured attention while the irrelevant stimulus with similar luminance was suppressed. Attentional capture by the partner target was further shown to be a function of the social context. The present dissertation, therefore, suggests that attentional control is flexible, as distractor attentional capture can vary depending on factors such as task predictability, previous experience, social value, and social context.

1 INTRODUCTION

We live in a complex visual world full of different objects and streams of information. To survive in such a world and respond properly to relevant events, we need to focus on a subset of objects at a time. In many circumstances, humans need to attend objects/events isolated from other people. However, considering the social characteristics of humans, we are very prone to interact with others and attend events together. In either of these scenarios, i.e. individual or joint task performance, we need to focus on the most relevant objects for our goal and ignore non-relevant items. For example, when we are watching a soccer match in a stadium with a friend, we need to continuously follow the ball to properly track the match despite the stadium being full of distractors. Fortunately, we are equipped with a rich attentional mechanism, namely *selective attention*, which filters out irrelevant information and directs our attention to goal-relevant object(s). In the soccer match example, the most important object might be the ball, although it's not the most salient object. Nevertheless, selective attention mechanism filters out all the salient lights and signs around the stadium and prioritizes the ball. Amongst all the noise, we might get more distracted by a commercial about our favorite coffee (because we have previous experience with it) which we drink every day. However, we immediately ignore it and redirect our attention to the ball. Our prediction regarding the ball's landing point is also a factor that helps us allocate our attention to the location containing the target (e.g. the ball) successfully (Posner, 1980). When watching the soccer match, we might want to discuss a situation with a friend who is sitting next to us. In this case, we both have to direct our attention to a common point (joint attention) to properly understand the other's intention (Michael, Sebanz, & Knoblich, 2016). All these processes, including following the ball and players, predicting events, communicating with our friend while tracking the ball, and ignoring the salient commercial can happen in a very short time window and would not be possible to perform without utilizing a multi-mechanism cognitive system.

The aim of the present dissertation is three-fold. The first goal is to investigate the neurophysiological mechanisms underlying of the interaction between previous experience (e.g., seeing a familiar advertisement in the stadium) and current goal (e.g., the ball) when an event is predictable (fully or partly) or unpredictable. More specifically, the aim is to understand the neurophysiological mechanisms underlying task preparation and investigating whether advance preparation can negate attentional biases caused by the previous experience. The second goal of this work is to introduce an algorithmic mathematical model to explain interaction between bottom-up, top-down, and previous experience in attentional selection during visual search tasks. The third goal of the present dissertation is to explain neurophysiological correlates of attentional deployment to the partner target when sharing a task with a co-actor depending on the social context.

1.1 Selective attention and the involved mechanisms

Within the last decade, numerous studies have shown that different control mechanisms work together to allocate attention to a point in space. The *bottom-up* control mechanism operates on visual features of the objects (e.g., color) and drives attention to the stimulus with the highest salience (Itti & Koch, 2001; Franconeri & Simons, 2003; Theeuwes, 1992, 2010, 2019). According to this mechanism, a salient item captures attention automatically, regardless of the current goal and intention. For instance, the participant's task in the additional singleton paradigm (Theeuwes, 1992) is to search for a diamond among circles or vice versa (i.e. a shape singleton). However, the presence of a color distractor slows down the response times (RTs). It implies that the salient distractor captures attention and delays attentional allocation to the target. On the other hand, goal-driven theories have suggested that attention is driven according to the current goal and intention of the observer in a *top-down* manner. According to this view, the observer's current goal determines whether a salient object captures attention or not (Folk, Remington, & Johnston, 1992; Folk & Remington, 1998; Eimer & Kiss, 2008; Theeuwes, 2010; Sawaki & Luck, 2010).

Nevertheless, some attentional biases can be explained neither by bottom-up nor by top-down control mechanisms. Awh et al. (2012) suggested that a third mechanism, namely *selection history*, competes against bottom-up and top-down to drive attention in an integrated priority map. Selection history refers to previous experiences and "the lingering effects of the last selection episodes" (Awh et al., 2012, p. 438). Reward history is one example of how selection history can be induced (Hickey, Chelazzi, & Theeuwes, 2010; Anderson, Laurent, & Yantis, 2011; Failing & Theeuwes, 2018). In a study by Anderson et al. (2011), two colors were associated with either low or high reward and participants had to learn this association throughout the training phase. Later, in the test phase, colors didn't carry any reward information and were only distractors while participants were searching for a shape singleton. The results showed high-value distractors caused slower responses than low-value distractors, implying that reward history affects target selection as well as attentional capture by the irrelevant distractor. Selection history can also be induced by inter-trial priming (Maljkovic & Nakayama, 1994; Wolfe, Butcher, Lee, & Hyle, 2003; Fecteau, 2007). According to Fecteau (2007), when the current target is the same as the target in the previous trial, a lingering effect resulting from the repetition of the relevant singleton causes more efficient task performance (Priming of Pop-out; PoP). Statistical regularities related to target and distractor location have also been shown to affect attentional processes (Wang & Theeuwes, 2018a, 2018b; Failing, Wang, & Theeuwes, 2019; Theeuwes, 2019; Ferrante et al., 2018). The target appearance at a highly probable location causes faster selection compared to when the target appears at relatively low probability locations (Ferrante et al., 2018). On the other hand, when a distractor appears at a high-probability distractor location, it captures less attention than when distractor appears at low-probability locations because the high-probable location is already suppressed due to previous history of having the distractor (Wang &

Theeuwes, 2018a, 2018b; van Moorselaar, Daneshtalab, & Slagter 2019; Di Caro, Theeuwes, & Della Libera, 2019).

Most relevant to the present dissertation, previous experience with a specific dimension of stimuli (e.g., color or shape) is another factor which induces individual selection history (Le Pelley, Beesley, & Griffiths, 2011; Feldmann-Wüstefeld, Uengoer, & Schubö, 2015; Kadel et al., 2017). In a study by Feldmann-Wüstefeld et al. (2015), when participants searched for a diamond-shaped target in an additional singleton paradigm, a color distractor captured more attention from those participants who had previous experience with the color dimension compared to those who had experience with the shape dimension. All the aforementioned studies indicate evidence for the impact of selection history on visual attention differently from bottom-up and top-down control mechanisms.

Recently it has become very common and useful to use electrophysiological biomarkers measured by electroencephalogram (EEG) to draw conclusions regarding the interplay between different control mechanisms in the level of brain activities (e.g., Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Henare, Kadel, & Schubö, 2020; Wang, van Driel, Ort, & Theeuwes, 2019; van Moorselaar et al., 2021). As such, EEG recordings were used in the present dissertation due to the high temporal resolution of EEG and well-stablished methods to extract EEG components correlated with attentional selection. The next section will focus on electrophysiological correlates of attentional selection.

1.1.1 EEG correlates of target selection and distractor suppression

Within the last three decades, researchers have developed methods to investigate neuronal mechanisms underlying attentional processing by recording brain activity with EEG during visual tasks. The N2-posterior-contralateral (N2pc) is the most prominent lateralized event-related potential (ERP) component, demonstrated by an enhanced negativity at posterior electrodes contralateral to the location of an attended item. It is attributed to the attentional selection of an item and occurs ~200 ms after stimulus onset. The N2pc component emerges when a target is laterally presented either with or without a salient distractor (Luck & Hillyard, 1994a; 1994b; Hickey et al., 2006; Burra & Kerzel, 2013; Woodman & Luck, 2003; Eimer, 2014; Liesefeld et al., 2017; Berggren & Eimer, 2018). Shorter onset latency and larger amplitude of the N2pc component have often been referred to as indices for faster and more efficient attentional deployment to the target (Mazza, Turatto, & Caramazza, 2009; Liesefeld et al., 2017; Kadel et al., 2017; Weaver, van Zoest, & Hickey, 2017). For instance, the N2pc amplitude occurring before saccade onset is larger when the saccade lands correctly on the target location than when it lands erroneously on the salient distractor (Weaver et al., 2017). In addition to the target, the salient lateral distractor has also been shown to capture attention and this is reflected in the distractor N2pc (Berggren & Eimer, 2018; Liesefeld et al., 2017; Feldmann-Wüstefeld et al., 2015).

Another prominent lateralized ERP component is the distractor positivity (Pd) component, which was first introduced by Hickey, Di Lollo, & McDonald (2009) as an enhanced positivity at posterior electrodes contralateral to the location of the to-be-ignored stimulus. The Pd component has been observed with different latencies after stimulus presentation, reflecting different types of suppressive mechanisms depending on the latency. The conventional late Pd component occurs 200 – 300 ms after stimulus onset and is associated with top-down inhibition of attentional capture by the salient distractor (Hickey et al., 2009; Sawaki & Luck, 2010; Kiss, Grubert, Petersen, & Eimer, 2012; Weaver et al.,2017; van Moorselaar & Slugter, 2019) and reflects reactive suppression of the distractor (Heuer & Schubö, 2020; Braver, 2012). In fact, for fast-response trials, lateral salient distractor in the additional singleton paradigm is shown to elicit the late Pd and indicates successful suppression of the distractor. On the contrary, when the suppression of the distractor is unsuccessful, the same stimulus does not elicit the late Pd (Jannati, Gasper, & McDonald, 2013). The late Pd component has also been attributed to suppression of the location which might contain a salient distractor (Heuer & Schubö, 2020). Furthermore, it indexes termination of attention after completion of target perception (Sawaki, Geng, & Luck, 2012; Jannati et al., 2013) and also the shifting of attention away from the salient distractor which has already captured attention (Feldmann-Wüstefeld et al. 2015; Henare et al., 2020).

Another early positivity occurs around 100 ms after stimulus onset that can be either a posterior positive contralateral (Ppc) or an early Pd component. The Ppc component is suggested to be linked to imbalance in sensory input (Fortier-Gauthier, Moffat, Dell’Acqua, McDonald, & Jolicoeur, 2012; Corriveau, Fortier-Gauthier, Pomerleau, McDonald, Dell'acqua, & Jolicoeur, 2012, Pomerleau, Fortier-Gauthier, Corriveau, Dell’Acqua, & Jolicoeur, 2014) or stimulus salience (Luck & Hillyard, 1994a). For instance, Jannati et al. (2013) observed the Ppc component emerged by the lateral distractor and its amplitude remained unaffected by the response speed. Crucially, when the ERP was locked to the target location, the Ppc was positive when target and distractor were on the same side. However, when target and distractor were on opposite sides, the Ppc had similar amplitude but was negative in direction. Importantly, when the target was a salient color singleton, Jannati et al. (2013) observed the Ppc. This indicated that the Ppc reflects only the imbalance of the search display and a response to the raw sensory input; it is not related to the early suppression of the salient distractor. On the contrary to the Ppc component, the early Pd component is suggested to reflect the early or proactive suppression of the salient distractor (Weaver et al., 2017; van Zoest, Huber-Huber, Weaver, & Hickey, 2021; Wang et al., 2019; van Moorselaar et al., 2021). A larger amplitude of the early Pd elicited by the salient distractor is shown to predict a more accurate eye movement to the target, suggestive of a more efficient target selection after stronger early distractor suppression (Weaver et al., 2017). Recently van Moorselaar et al. (2021) used a version of the additional singleton paradigm where target and distractor were fixed in some blocks, and mixed in other blocks. In half of blocks (“spatial bias blocks”) there was a high-probability distractor location. In these blocks, the distractor always elicited an early Pd, but only in participants who didn’t learn the high probability distractor location. Based on these results, van Moorselaar et al. (2021) suggested that the early Pd might reflect an active distractor suppression mechanism via intertrial priming. Furthermore, the high-probability distractor location is shown to elicit the early Pd, irrespective of the stimulus which appears in that location (target or distractor; Wang et al., 2019). That is, the high-probability distractor location is suppressed proactively, a mechanism which is reflected in the early Pd components (Wang et al., 2019; Weaver et al., 2017). Or when the feature of the distractor is cued, less distractor suppression is required as it is reflected in the amplitude reduction of the early Pd because the distractor loses its power in capturing attention (van Zoest et al., 2021).

Besides these well-defined ERP components associated with attentional selection, EEG oscillations are also used to index attentional processes. By spectral decomposition of EEG time series data using mathematical methods such as the Fourier transform, the power of individual frequencies can be extracted. For electrophysiological research, EEG frequencies are labeled as delta (1 – 4 Hz), theta (4 – 8 Hz), alpha (8 – 14 Hz), beta (14 – 30 Hz), and gamma (>30 Hz) bands (Clayton et al., 2015). Oscillations in the range of alpha-band over the posterior cortex have mainly been suggested as a neurophysiological marker of attentional processes (Clayton, Yeung, & Kadosh, 2018; Hanslmayr, Gross, Klimesch, & Shapiro, 2011; Klimesch, 2012), making alpha-band oscillations of particular interest for the present dissertation. Various physiological sources have been implicated as generators of alpha-band oscillations, such as the thalamus (Liu et al., 2012) and thalamocortical loops (Hughes et al., 2004). For instance, fluctuation of the alpha-band amplitude is positively correlated with BOLD signals recorded from the thalamus using fMRI (functional magnetic resonance imaging; Sadaghiani et al., 2010).

A large body of literature has attributed the decrease in alpha-band power to attentional deployment to the target. In the scope of visuospatial attention, when a target location is cued to be in the right or left visual field, alpha-band power is shown to decrease over the visual cortex contralateral to the attended location to a stronger degree than that over the ipsilateral hemisphere (Worden et al., 2000; Thut, Nietzel, Brandt, & Pascual-Leone, 2006; Doesburg et al., 2016; Noonan et al. 2016; Wildegger, van Ede, Woolrich, Gillebert, Nobre, 2017; van Moorselaar & Slagter, 2019). These studies showed that underlying neural processing of the alpha-band plays a prominent role in preparatory processing of the target. Other researchers have further examined whether the alpha-band plays an active role in target processing (van Diepen et al., 2016; Bacigalupo & Luck, 2019). For instance, Bacigalupo & Luck (2019) asked participants to search for a circle with a specific color as the target and report whether the gap was on the top or bottom. Their results showed that target presentation in the right or left visual field elicited the N2pc component and reduced the alpha-band power over the occipital area contralateral to the target location. Importantly, when the target appeared in the lower visual field, both the N2pc amplitude and alpha reduction were stronger than when the target appeared in the upper visual field. Besides this, the time window of the N2pc component overlapped with the time window of contralateral alpha-band reduction. This pattern of data suggests that underlying neural processing of alpha band is involved in active target processing. Further, a stronger reduction of contralateral alpha relative to the target location in correct than in incorrect responses suggests a direct impact of alpha modulation on behavior (Wöstmann et al., 2016).

While there is ample evidence supporting the idea that the alpha-band power is involved in target processing, the engagement of the alpha-band power in distractor processing is dubious (Schneider et al., 2021). Noonan et al. (2016) found that when the exact location of the distractor is cued, task performance improves only when the cued location was fixed over the experiment. This finding indicates that cumulative experience regarding the distractor location facilitates task performance. In the same condition, however, no alpha modulation was found in the interval before stimulus presentation. The absence of the alpha-band power changes when the distractor location was cued suggested that alpha-band power doesn't mediate distractor suppression. This idea was further supported by van Moorselaar et al. (2019; 2021) who manipulated spatial regularity of the distractor by repetitively presenting the distractor in a location (van Moorselaar & Slagter, 2019) or by presenting the distractor more often in one location in the display (high-probability location; van Moorselaar et al., 2021). Van Moorselaar & Slagter (2019) didn't observe any modulation of pre-stimulus alpha-band power when distractor location was known to be repeated from trial-to-trial, although this repetition reduced the need for distractor suppression as well as RTs. The same authors further showed that combination of spatial and feature expectations of distractor also did not elicit any pre-stimulus alpha modulations although it improved task performance and distractor suppression (van Moorselaar et al., 2021). This set of finding casts a dubious shadow on the involvement of alpha-band power in distractor suppression.

Contrary to the above-mentioned studies, recent works have succeeded in showing the involvement of alpha-band power increases in distractor processing brain regions (Jensen & Mazaheri, 2010; Händel, Haarmeier, & Jensen, 2011; Kelly, Lalor, Reilly, & Foxe, 2006; van Zoest et al., 2021; Wöstmann et al., 2019; Wang et al., 2019). A prominent theory is "gating by inhibition" which suggests that increased power of posterior alpha-band reflects regional inhibition of visual cortex to suppress task-irrelevant information (Jensen & Mazaheri, 2010). Suppressing the irrelevant stimuli through increased alpha-band power has a direct impact on behavior. In a study by Händel et al. (2011), participants were cued to covertly attend to either left or right visual field. Patches of moving dots were presented on both sides in which a proportion of dots had the same direction. Later, participants were asked to report the direction of movement in one of the hemifields (valid vs. invalid). Their results showed increased alpha-band power contralateral to the unattended location and reduced alpha-band power contralateral to the attended location. Crucially, this lateralization predicted the participant's performance when they were probed to report the movement direction of the unattended hemifield. This finding indicated that increased alpha-band power reflects a suppressive mechanism of unattended item/location. Besides this active suppressive characteristic of alpha band power, oscillations in the range of alpha have been shown to be involved in proactive suppression of a visual (van Zoest et al., 2021) or auditory (Wöstmann et al., 2019) distractor. For instance, Wöstmann et al. (2019) presented distractor on one of the hemifields and target on the vertical meridian. This presentation technique helped in isolating the mechanisms involved in distractor processing from those involved in target processing. Their results showed that anticipation of the distractor on either right or left side increases contralateral and decreases ipsilateral alpha-band power at parietal brain regions.

Providing participants with the location of the distractor, either explicitly (van Zoest et al., 2021) or implicitly (Wang et al., 2019) triggers a proactive distractor suppression mechanism which is reflected in increased pre-stimulus alpha-band power contralateral to the high-probable distractor location. For instance, van Zoest et al. (2021) showed that the known distractor location or feature of the distractor before stimulus onset increases pre-stimulus alpha-band power. Moreover, Wang et al., (2019) showed that this information about the location doesn't need to be explicit, but even implicitly learnt distractor location increases pre-stimulus alpha-band power at occipital regions. To show this, they presented the distractor more often in one lateral location in additional singleton paradigm unbeknownst to the participants, and this induced increased pre-stimulus alpha-band contralateral to the high-probable distractor location. All in all, these findings support the role of alpha-band power in regulating distractor suppression and target selection either in pre-stimulus (proactive) or post-stimulus (reactive) intervals.

1.1.2 Interplay between top-down, bottom-up, and selection history

So far, several theoretical and computational models have been proposed to explain attention deployment to, or suppression of an object or a location in space. These theories have mainly focused on the interaction between bottom-up and top-down mechanisms (Bacon & Egeth, 1994; Theeuwes, 2010; Sawaki & Luck, 2010; Gaspelin, Leonard, Luck, 2015). However, the interplay between selection history and other control mechanisms have not been well-investigated so far. As it is suggested, besides the physical salience and current goal, selection history also feeds into an integrated priority map to select an object in an environment (Awh et al., 2012; Theeuwes, 2019). In such an integrated priority map, each sensory input (bottom-up), observer's intention (top-down), and lingering selection bias (selection history) generates a signal to drive attention. The signal which overshadows the others could drive attention in a winner-take-all manner (Theeuwes, 2019; Itti & Koch, 2001).

The rapid-disengagement account proposes that spatial attention is initially directed to the most salient singleton on the search array in a bottom-up fashion. When it becomes evident that the identity of the singleton is a distractor, attention is immediately disengaged and is redirected to the target (Theeuwes, 2010). However, this view has since been challenged by other studies (Wykowska & Schubö, 2011; Gaspelin et al., 2015). Using the N2pc component, Wykowska & Schubö (2011) tracked whether the allocation of attention was on the target or the distractor. They observed that the N2pc was elicited by the target, but not the distractor. Also, the N2pc amplitude was not different when the target and distractor were on opposite sides as compared with when they were on the same side (see also Jannati et al., 2013), although the N2pc onset was later when singletons were on the opposite sides than when they were on the same side. These results indicated that attention was successfully directed to the target without initially being captured by the salient distractor. The delayed N2pc observed when singletons were on opposite sides, however, indicated that singletons competed to capture attention which caused only delayed attentional allocation to the target and not attention capture by the distractor (i.e., nonspatial filtering costs, Folk & Remington, 1998, 2006). Therefore, when participants know the exact feature of the target, the top-down control mechanism gains the potency to control the bottom-up attentional capture so that attention is directly deployed to the target.

Another hybrid theory, namely the signal-suppression hypothesis, posits that both bottom-up and top-down controls incorporate the allocation of attention when a salient distractor is present (Stilwell, Egeth, & Gaspelin, 2022; Gaspelin et al., 2015; Sawaki & Luck, 2010). According to this model, a salient singleton generates an attend-to-me signal in a bottom-up fashion irrespective of its match with attentional control settings. However, it is the top-down mechanism that determines whether attention shifts to that singleton, as follows: If the singleton matches the target template, attention is deployed to the location of the singleton which manifests in the N2pc component. However, if the singleton doesn’t match the target template, top-down control suppresses the non-relevant salient singleton and this suppression is reflected by the Pd component (Stilwell et al., 2022; Sawaki & Luck, 2010).

Other studies, using computational modeling, have tried to further clarify how bottom-up and top-down control mechanisms interplay to select a target or suppress a distractor (for a review see Itti & Borji, 2015). Initially, Itti, Koch, & Niebur (1998) suggested a bottom-up model for visual attention based on the physical salience of stimuli. In the approach used by Itti et al. (1998), physical features of stimuli are extracted and divided into three conspicuity maps namely, color map, intensity map, and orientation map. Later, these three maps are linearly combined to form a master saliency map. In the master saliency map, in a winner-take-all manner, the most active location captures attention while the other locations are suppressed. Ever since the model introduced by Itti et al. (1998) has been combined with top-down models to simulate the combined effects of physical salience and the observer’s intentions on human attention (Peters & Itti, 2007; Borji, Sihite, & Itti, 2014; Tanner & Itti, 2019). To this end, Peters & Itti (2007) used the model introduced by Itti et al. (1998) to describe the bottom-up module of their model and combined it with a top-down module to predict the observer’s gaze when playing a video game. The top-down module of Peters & Itti’s model was based on the idea of ‘gist’ (the ability of participants to roughly describe the overall layout of an image after a brief presentation) and functioned as follows: During a training phase, the low-dimensional feature vectors from each video frame are extracted and the top-down module is trained to pair them with the corresponding eye position. Later, the trained top-down module constitutes a gaze density map from unseen video frames and the bottom-up module provides a gaze density map based on low-level visual features (e.g., orientation). Their results showed that top-down model narrowed down the number of the locations which were predicted by the bottom-up model to be the eye position. Prediction of the eye position was most precise when bottom-up and top-down models were combined (Peters & Itti, 2007).

Despite the ample number of studies on bottom-up and top-down modeling, not many studies have computationally modeled the effects of selection history on attentional selection. A large body of recent research has shown that various forms of selection history affect top-down target selection or distractor suppression (Le Pelley et al., 2011; Feldmann-Wüstefeld et al., 2015; Ferrante et al., 2018; Wang & Theeuwes, 2018a; 2018b, Wang et al., 2019; Henare et al., 2020; van Moorselaar et al., 2019; 2021). Acquired experience using associative learning of a specific dimension impacts subsequent target selection when the used-to-be predictive dimension appears to be a distractor (Le Pelley et al., 2011; Feldmann-Wüstefeld et al., 2015). Importantly, selection history continues to compete against the top-down mechanism even when participants are provided with foreknowledge about the upcoming task using cueing or predictable trial sequence (Kadel et al., 2017) or voluntary task selection (Henare et al., 2020). Statistical regularities about the high-probable location of the distractor also impair target selection if the target appears in that high-probable location of the distractor (Ferrante et al., 2018; Wang & Theeuwes, 2018a; Wang et al., 2019; van Moorselaar et al., 2019; 2021). According to these recent studies, it seems that selection history mostly competes against top-down influences to direct attention toward the stimulus containing a feature dimension that matches the observer’s previous experiences. Therefore, it seems necessary to computationally describe the interplay between selection history and the other two control mechanisms. Study III of the present dissertation aims to fill this gap in modeling studies by presenting a model to computationally describe how selection history influences attentional selection.

1.2 Predictability and its impact on attentional control

Predictability about upcoming events has been shown to enhance task performance by enhancing target selection and distractor suppression (van Zoest et al., 2021; Heuer & Schubö, 2020; Burra & Kerzel, 2013). According to a large body of studies, sequential structure (Koch, 2003; Heuer et al., 2001; Roger & Monsell, 1995; van Moorselaar & Slagter, 2019), explicit cues (van Zoest et al., 2021; Heuer & Schubö, 2020; Meiran, 1996), and voluntary task switching (Arington & Logan, 2004, 2005; Yeung, 2010; Henare et al., 2020) are common methods to manipulate predictability in an experimental setting. In sequential structure, participants implicitly or explicitly learn the regularities embedded in the repetitive cycles of tasks, so they can predict the next task based on the current task (Koch, 2003; Heuer et al., 2001; Roger & Monsell, 1995). For instance, in the study by Roger & Monsell (1995), the stimulus in each trial was presented in one of the quadrants of the display and its location changed clockwise when moving to the next trial. Two adjacent quadrants were associated with task “A” and the other two quadrants were associated with task “B”. This provided participants with the predictable task sequence of AABBAA. In a predictable task sequence, predictability triggers advanced preparation in an endogenous manner (Roger & Monsell, 1995). In fact, in a predictable task sequence, an internal cue is constituted “based on memory of previous tasks and future intentions” (Koch, 2003, p. 1). This internal cue activates a preparatory mechanism by which the participant can proactively reconfigure the attentional set required in the upcoming trial. The next sub-section elaborates on how the attentional set can be reconfigured in advance when switching between two different tasks. This is important, because a fundamental goal of the present dissertation is to investigate whether strategic and proactive preparation can eliminate the attentional biases induced by selection history (Studies I, II).

1.2.1 Task-set reconfiguration in task-switching paradigms

A task-switching paradigm was first introduced almost one hundred years ago and since then, it has been used to study the dynamics of cognitive processes. In a task-switching paradigm, trials in which the task switches from the previous trial are called switch trials, and trials in which the task repeats the previous trial are called repetition trials. The difference in RT between switch and repetition trials is called switch cost (Monsell, 2003). *Task-set reconfiguration* has been suggested as a switch-specific time-consuming process that causes the longer RT in switch than in repetition trials (Mayr & Keele, 2000; Monsell, 2003; Monsell & Mizon, 2006). Task–set reconfiguration refers to a set of processes to: recall the rules related to the new task from long–term memory, overcome the inhibition of the new task set, adjust the effector to respond, and suppress activities related to the old task (Rogers & Monsell, 1995; Mayr & Keele, 2000; Monsell & Mizon, 2006).

Providing participants with foreknowledge about the upcoming task and also with enough time to utilize this foreknowledge in the task-switching paradigm engages the task-set reconfiguration *before* stimulus onset and facilitates task performance (for a discussion see Vandierendonck, Liefooghe, & Verbruggen, 2010). This advance preparation is more beneficial in switch trials which require stronger reconfiguration than in repetition trials. Due to this, advance preparation reduces RT in switch trials more than in repetition trials, which results in decreasing switch cost (Rogers & Monsell, 1995; Monsell & Mizon, 2006). However, switch cost doesn’t disappear completely even after a long preparation interval (e.g. Monsell & Mizon, 2006, Exp. 2 & 3). The persistence of a switch cost, despite there being enough time for advance preparation in a predictable task sequence, indicates the presence of a persisting interference in task switching. A critical example of this interference can be stimulus-response mapping. When the same response keys are used for two different tasks, the response is slower in incongruent (stimuli mapped to different response buttons) than in congruent (stimuli mapped to one response button) trials even in a predictable task sequence (Roger & Monsell, 1995; Monsell, Sumner, & Waters, 2003). In fact, participants cannot prepare for an exact button press until the stimulus appears, no matter how much time they have had to prepare (reactive control mechanism; Braver, 2012). Therefore, predictability seems to facilitate only those cognitive processes which can be achieved before the occurrence of the next task.

Accordingly, a two-stage model of task-set reconfiguration was proposed (Rogers & Monsell, 1995; Mayr & Kliegl, 2000; Braver, 2012; for a recent review see Koch, Poljac, Müller & Kiesel, 2018). Based on this model, the first stage referred to as the endogenous component of task-set reconfiguration, occurs before a predictable stimulus in the form of a proactive process representing cognitive flexibility and advance preparation. This proactive control mechanism allows observers to resolve the potential interference before it occurs (Braver, 2012). The second stage called the exogenous component of task-set reconfiguration, occurs after stimulus onset and doesn’t allow for a complete readiness in a predictable task sequence before stimulus onset. This reactive control mechanism engages after stimulus onset and drives attention to resolve the interference after its onset (Braver, 2012). One crucial question which remains unanswered is, to which extent the residual biases induced by previous experience can be eliminated by advance preparation? How does the prediction reliability about the next trial counteract with selection history effects? These questions are going to be answered in Studies I and II using manipulation of selection history and task predictability.

Looking at brain activity before stimulus onset using EEG is a useful approach to directly assess proactive preparation. Several studies have directly assessed proactive preparation using pre-stimulus alpha-band power when switching between tasks (Gladwin & de Jong, 2005; Poljac & Yeung, 2014; Foxe, Murphy, & De Sanctis, 2014; Wolff, Zink, Stock, & Beste, 2017; Proskovec, Wiesman, & Wilson, 2019). These studies have commonly found reduced pre-stimulus alpha-band powers over frontocentral and parieto-occipital regions in the brain when switching compared to when repeating a visual task, a reflector of preparatory process. Based on this finding, it is plausible to use pre-stimulus alpha-band power in study I to directly assess: a) whether fixed and random task sequences induce proactive preparation, and b) how selection history impacts proactive preparation.

1.2.2 Task predictability facilitates target selection and distractor suppression

A prominent benefit of task predictability is reducing surprise when facing an event, and the subsequent reduction in prediction errors (Friston, 2009). A simple strategy to reduce prediction error is attending to the surprising events (Pearce & Hall, 1980). Stronger attendance to a surprising, unpredictable event is reflected in greater sensory responses (Heuer & Schubö, 2020). For instance, when the feature of the target and distractor was not predictable, Burra and Kerzel (2013) observed a strong neuronal response elicited as a distractor N2pc which didn’t emerge when the features of the target and distractor were predictable. In the same vein, Feldmann-Wüstefeld & Schubö (2016) observed in a heterogonous visual search task, that RTs were faster in the predictive distractor repetition trials than in random distractor repetition trials. Aligned to this behavioral finding, their

ERP results showed monotonically decreasing distractor N2pc amplitudes with repetition of distractor color. Critically, predictive repetition of the distractor color had no impact on the target N2pc and Pd. The authors concluded that the predictable distractor contributes to reducing distractor attentional capture, supporting the idea that predictability reduces surprise, which is reflected in decreased neural response to a stimulus.

Improved attentional selection has not only been observed through the target/distractor feature predictability (e.g. Feldmann-Wüstefeld & Schubö, 2016; Burra & Kerzel, 2013; Arita, Carlisle, & Woodman, 2012; Bacon & Egeth, 1994), but foreknowledge about the target location (Posner 1980; Ruff & Driver, 2006; Noonan et al., 2016; Wildeger et al., 2017) and distractor location (Ruff & Driver, 2006; Noonan et al., 2016; van Moorselaar et al., 2019;2021; Heuer & Schubö, 2020; Wang et al., 2019). For instance, in the study by Heuer and Schubö (2020), predictability about the location of the distractor caused less need for distractor suppression as shown by reduced amplitude of the late Pd in trials with predictable cues than in trials with unpredictable cues (see also van Moorselaar & Slagter, 2019). Furthermore, more focused attentional deployment to a predictable target is indexed by the increased amplitude of the N2pc component in predictable than in unpredictable condition (Burra and Kerzel, 2013; Liu, Lin, Zhao, & Roberson, 2016). In sum, predictability regarding the target and distractor facilitates task performance via either reduced distractor attentional capture (Feldmann-Wüstefeld & Schubö, 2016, Burra & Kerzel, 2013), improved distractor suppression (Heuer & Schubö, 2020), or improved target selection (Burra & Kerzel, 2013, Liu et al., 2016). Critically these processes are highly influenced by proactive preparation which already starts before the onset on the predictable stimulus.

As it was pointed out earlier, EEG measures are the proper tools to directly measure (pro)active target selection or distractor suppression. Using this approach, brain activity can be recorded with a high temporal resolution from some time before stimulus onset, when participants are possibly preparing for target/distractor handling, until after termination of attentional processes and performing the task. Pre-stimulus alpha-band power (Payne, Guillory, & Sekuler, 2013; Wildegger et al., 2017; Wang et al., 2019; van Zoest et al., 2021) and the early Pd component (van Moorselaar et al., 2019; 2021; van Zoest et al., 2021; Weaver et al., 2017) are two direct measures of proactive distractor suppression frequently used in recent studies. For instance, Payne et al. (2013) presented two Gabor patches consecutively where each stimulus was cued to be attended or to be ignored. The task of the participant was to reproduce the spatial frequency of the attended stimulus. Due to the design of their task, when the first Gabor was cued to be attended, the suppression of the second stimulus was already predictable. In this condition, their results showed greater pre-stimulus alpha-power before the predictive, distracting stimulus. Furthermore, increased alpha-band power was shown to be correlated with the reduced influence of the nontarget in the reproduced spatial frequency. This finding fits nicely with the gating by inhibition theory (Jensen & Mazaheri, 2010), supporting the notion that neurons representing the distractor are inhibited to avoid any conflict between the target and distractor representation. This proactive distractor suppression reflected in pre-stimulus alpha-band increase has a direct impact on post-stimulus distractor suppression (Van Zoest et al., 2021). When location or feature of the distractor was validly cued, van Zoest et al. (2021) showed that the increased pre-stimulus alpha-band resulted in the decreased amplitude of the distractor N2pc or the early Pd, respectively. They speculated that implementation of the proactive distractor suppression directly reduces attentional capture by the distractor or need for distractor suppression. In fact, proactive suppression could reduce the saliency of the upcoming distractor, resulting in easier ignorance of the distractor (Liesefeld & Müller, 2019).

However, other studies have failed to link proactive distractor suppression to pre-stimulus alpha-band oscillations (Noonan et al., 2016; van Moorselaar et al., 2019; 2021). For instance, Noonan et al. (2016) cued the location of the distractor and observed enhanced performance only when distractor presence was blocked (i.e., all trials in the block contains the distractor). This suggests that proactive distractor suppression is not a flexible top-down process, but rather a process requiring valid and precise prediction of the distractor presence. Moreover, their electrophysiological results showed reduced amplitude of P1 at regions processing the expected distractor, indicating less selection of the distractor. These findings were in agreement with the predictive coding account, proposing attenuated neural response to the predictive stimulus (Summerfield & de Lange, 2014). However, the alpha-band power in the interval prior to the predictive distractor didn’t show any significant modulations in power (same was shown by van Moorselaar et al., 2019; 2021). This finding suggests that pre-stimulus alpha is not involved in proactive distractor suppression. In sum, predictable distractor facilitates task performance through less need for distractor suppression, but the findings on the link between proactive distractor inhibition and pre-stimulus alpha are mixed.

The first two studies of the present dissertation (Studies I & II) investigate the influence of task predictability on proactive preparation and attentional selection in presence of selection history. Recording and analyzing the EEG data in the intervals before (Study I) and after stimulus onset (Studies I & II) help to look at specific mechanisms involved in proactive preparation, target selection, distractor attentional capture, and distractor suppression. Based on the above-mentioned studies, pre-stimulus alpha-band, the early Pd, the late Pd, and N2pc components are used to test the hypotheses in each study.

1.3 Joint action

A large proportion of studies on visual attention have focused on situations with only one participant performing a task in an isolated condition, such as the studies cited in section 1.1 and 1.2. However, outside the laboratory, we continually interact with other people and often share tasks together. The kind of interaction in which two or more individuals coordinate their actions, both spatially and temporally, to accomplish a task is called *joint action* (Sebanz et al., 2006a). For instance, when a player aims to pass the ball to a teammate, both players have to direct their attention to the ball to achieve a successful interaction. Furthermore, the player needs to correctly anticipate the action and movement direction of the other to perform with minimum error. Accomplishing this complex process requires players to form a representation about the action of each other, which has been referred to as *shared task representation* (Ramnani & Miall, 2004). The basic mechanism for the representation of a partner's action is directing attention to the point in space to which the interacting partner is attending, namely *joint attention* (Sebanz et al., 2006a; Freundlieb, Sebanz, & Kovács, 2017). Joint attention enables agents to form a representation of the partner's action in a very similar way to the representation of their own action. This section will elaborate on the definition of joint attention, interaction between joint action partners, and the influence of the social context on this interaction. In the present dissertation and specifically in study IV, the label *agent* refers to the person whose data was recorded, analyzed, and interpreted. The label *partner* refers to the co-actor whose EEG was not recorded.

1.3.1 Joint attention in joint action

The ability of joint attention allows us to track the focus of attention of the partner and allocate our attention to that point. Common allocation of attention to a point in space helps individuals to establish cognitive inferences regarding goals, intentions, and actions of their partners, resulting in the successful performance of a shared task. According to the action co-representation account, when agents observe the partner target, they form a co-representation of their partner's action (Sebanz et al., 2003, 2006a), and this co-representation has been shown to influence visual attention of the agent from very early on after stimulus onset (Baess & Prinz, 2015). When sharing a task, Baess & Prinz (2015) showed that the presentation of an object requiring a response from both co-actors activates a larger amplitude of the frontocentral N1 than the presentation of an object which requires a response from one actor. Larger amplitude of the N1 component is an EEG marker indicating stronger attentional deployment to the target (Vogel & Luck, 2000). Therefore, when sharing a task, co-representation of the partner action requires the agent to deploy attention to the partner target, although the partner's performance has no influence of the task or the final performance outcome of the agent. Utilizing the EEG biomarkers associated with attentional selection thus seems to be an appropriate tool to investigate neural correlates of the partner target processing in joint action tasks.

As mentioned earlier, the underlying neural process of EEG oscillations in the range of alpha-band is involved in attentional deployment to the target (Klimesch, 2012; Bacigalupo & Luck, 2019) or suppression of the distractor (Wöstmann et al., 2019; Bengson, Liub, Khodayari, & Mangun, 2020). In the scope of social coordination, reduced alpha-band power has been observed when participants perform a movement coordination (Naeem, Prasad, Watson, Kelso, 2012) or an attention coordination task (Lachat, Hugueville, Lemaréchal, Conty, & George, 2012). For instance, Lachat et al. (2012) assumed that jointly attending to the same object requires interpersonal coordination and mutual awareness. Therefore, they expected reduced alpha-band power when actors attended to the same target. To test this hypothesis, they recorded EEG data from pairs of participants who were sitting face-to-face. Participants directed their attention toward either the same (joint attention condition) or different (single attention condition) LED lights. The results showed reduced alpha-band power over posterior regions in the joint relative to the single attention condition. As the authors speculated, attending to the shared target and the other's gaze in the joint condition reduced alpha-band power, while the suppression of the partner target and the partner's gaze in single attention condition increased alpha-band power (according to gating by inhibition, Jensen & Mazaheri, 2010). This finding suggests that, the neurophysiology underlying mechanism(s) involved in joint attention can be observed in the posterior alpha-band power recorded via EEG and forms the motivation for utilizing alpha-band oscillations in study IV.

Observing another individual's action induces an action tendency in the observer to perform that action even if it's not the one's turn to act (de Bruijn, Miedl, & Bekkering, 2008; Sebanz, Knoblich, Prinz, & Wascher, 2006b; Tsai, Kuo, Jing, Hung, & Tzeng, 2006). This tendency towards an action imitation is related to a population of neurons in the brain, namely mirror neurons (Rizzolatti & Craighero, 2004; Buccino, Binkofski, & Riggio, 2004). When an observer sees an action produced by another individual, neurons that represent that action fire in the observer's premotor cortex and this neural firing automatically produces a representation of the observed action (Rizzolatti & Craighero, 2004; Hauswald, Tucciarelli, & Lingnau, 2018). This implies that, when pairs of individuals perform a task together in a joint action setting, any action produced by a co-actor induces a tendency toward producing the same action in the actor (e.g., action co-representation account). Further, observing a partner target which is associated with the partner's action might induce different neural activation than observing a non-relevant distractor, although both are task-irrelevant for the observer (Atmaca, Sebanz, & Knoblich, 2011; Saunders, Melcher, & van Zoest, 2019). The main aim of Study IV is to investigate the neurophysiological correlates of attentional deployment to the partner target. Moreover, Study IV investigates how the processing of the partner target differs from the processing of the non-relevant distractor despite the fact that they are both non-targets for the agent.

1.3.2 Impact of the partner target on the agent's attention

A common approach to investigate the influence of the partner target on the agent's attentional selection in joint action involves two participants in a shared task and asking each of them to respond only to their own target. For instance, a social version of the Simon task (Simon, 1969) has often been used (Sebanz et al., 2003) wherein two participants share a Simon task and each person is supposed to respond to the non-spatially defined targets using spatially defined responses. The agent target can appear on the same side as the agent sitting location (i.e., compatible trials) or on the same side as the partner's sitting location (i.e., incompatible trials). As a consequence of this arrangement, response time is slower in the incompatible than in the compatible trials (joint Simon effect). These findings have been explained by different theories such as the action co-representation account (Sebanz et al., 2003), the spatial response coding account, and the referential coding account (Dolk, Hommel, Prinz, & Liepelt, 2013).

From the action co-representation account's perspective, when participants share a task, they represent their own and the other's stimulus-response rules and action plans. These action representations come with the representation of the spatial dimension of the responses. Therefore, a mismatch between spatial response feature and spatial stimulus feature results in response interference, while a match between the abovementioned features facilitates task performance (Sebanz et al., 2003; Tsai, Kuo, Jing, Hung, & Tzeng, 2006; Sebanz et al., 2006b; Sebanz, Rebbechi, Knoblich, Prinz, & Frith, 2007). The action co-representation account considers the human-being partner as an important factor in development of the joint Simon effect. Analogous to this idea, later studies showed the reduced size of the joint Simon effect when the co-actor was not human-like anymore (Müller et al., 2011; Stenzel et al., 2012). For instance, the joint Simon effect disappeared when the humanoid robot co-actor was described to be machine-like and it appeared when robot was described to be human-like (Stenzel et al., 2012).

However, there are some other scenarios that the joint Simon effect cannot be justified by action co-representation account. For instance, spatial compatibility effect is observed when participants, stimuli, and the response keys are either horizontally or vertically aligned, but disappears when this alignment is disrupted (Dittrich et al., 2012; 2013). That is, when participants sit side-by-side, no joint Simon task is observed when the stimuli are horizontally aligned and the response keys are vertically aligned. This is not trivial because action co-representation account would predict spatial compatibility effect, as long as side-by-side participants share a task (Sebanz et al., 2003, 2006). Dittrich and colleagues, therefore, introduced the spatial response coding account, which posits that the compatibility effect in the joint Simon task is due to the overlap between the spatial dimension of the stimuli, response keys and participants sitting location (Dittrich et al., 2012, 2013). One other scenario that cannot be justified by the action co-representation account is when the co-actor is an inanimate object. For instance, Dolk et al. (2013) observed a robust spatial compatibility effect even when the co-actor was a Japanese waving cat. Following this observation, Dolk and colleagues suggested the referential coding account positing that the presence of a salient event (e.g. the partner) provides the agents with a spatial reference frame by which the agents code themselves and their response as ‘left’ or ‘right’. Subsequently, the overlap between this re-introduced response dimension and the task-irrelevant spatial dimension, triggers the spatial compatibility effect (Dolk et al., 2013, 2014; Lien, Pedersen, & Proctor, 2016).

In joint action settings, the partner target influences an actor's performance differently from neutral distractors (Atmaca et al., 2011; Saunders et al., 2019). This is interesting because both the partner target and neutral distractors are task-irrelevant for the agent and both are expected to be suppressed in a top-down fashion

(Theeuwes 2010). However, recent studies have shown that the presence of the partner target (Atmaca et al., 2011) or a feature related to the partner target (Saunders et al., 2019) impairs the agent's task performance. For instance, when participants share a task, the task performance is faster when an agent target is flanked by neutral distractors than when it is flanked by the partner target. As an explanation, Atmaca et al. (2011) speculated that the agents represented the partner's task in addition to their own task, which resulted in response interference.

In nearly all joint action instances in real-life, humans have to either cooperate to accomplish a shared goal or compete against each other to achieve a better outcome compared to a competitor. In a joint action setting with a positive or a cooperative relationship, the agents integrate their actions with their representation of the partners' actions, and this increases the impact of a partner target on the agent's performance (self-other integration). In a competitive relationship, however, the agents try to ignore their partner target and focus on their own target (Hommel et al., 2009; Ruissen & de Bruijn, 2016). Based on these different principles, attentional deployment in the cooperative condition would differ from that in the competitive condition. Unfortunately, previous studies have provided inconsistent findings regarding the effect of social context on the deployment of attention in joint action tasks. For example, some authors have used different variations of the joint Simon task (Sebanz et al., 2003) and have shown a larger joint Simon effect when partners share a task in the cooperative than in the competitive condition (Colzato, de Bruijn, & Hommel, 2012; Ruissen & de Bruijn, 2016; Mendl, Fröber, Dolk, 2018) or in a friendly than in an unfriendly social context (Hommel et al., 2009). On the other hand, Ruys & Aarts (2010) reported a similar joint Simon effect between cooperative and competitive conditions which were significantly larger than the joint Simon effect in the independent condition. Due to these inconsistencies in the literature, it remains unclear as to what extent the different types of social contexts affect human performance at behavioral and neuronal levels. Study IV strives to elucidate differences in the processing of the partner target between the cooperative and competitive conditions by recording and analyzing ongoing EEG oscillations.

1.4 Aims and experimental approaches

From a broad point of view, the present dissertation is aimed at understanding how factors such as previous experience, proactive preparation, task predictability, social value and social context shape attentional control. The first two studies of the present dissertation use experimental approaches to investigate how previous experience, as a form of selection history, interplay with task predictability in shaping attentional allocation during a visual search task. In the third study, a computational approach is used to describe the interplay between selection history, physical salience and the observer intention in the integrated priority map. Finally, the fourth study examines how participants deploy attention in a visual search task when they are sharing a task with a partner in joint action settings either in a cooperative or competitive social context.

The present dissertation uses different variations of the additional singleton paradigm (Theeuwes, 1992) to investigate the influence of the aforementioned factors on visual attention. The additional singleton paradigm was originally developed to examine specific mechanisms involved in target and distractor processing. The version of this paradigm used in Studies I – III consists of a diamond-shaped target among seven non-target circular distractors. In some trials, the color of one circle is red (color singleton). The participant's task is to search for the shape target and report the orientation (vertical vs. horizontal) of the embedded line. The salient color singleton has been shown to capture attention and is reflected in slower task performance in distractor-present than in distractor-absent condition (Theeuwes, 1992). In Studies I & III, the target and the salient distractor could appear on the same or opposite hemifields. In Study II, in distractor-present trials, one of the singletons (either the shape target or the color distractor) could appear on the vertical meridian while the other singleton on the horizontal meridian.

In Study IV, a modified version of the additional singleton paradigm was shared between two participants. The paradigm consisted of eight Gabor patches from which two were colored and six were gray. In total, there were four different colored Gabor patches (red, blue, orange, purple; Fig. 5B) which could be assigned to an agent target, a partner target, and two non-relevant distractors. Importantly, all the color stimuli were of the similar luminance. Participants in each pair were supposed to search for the stimulus in their assigned color and report the orientation of the target Gabor patch using a mouse click on a response display. If a participant's target was absent, they needed to click on a "No target" button on the response display.

In order to quantify the deployment of attention in Studies I, II and IV, two different types of data were measured. Behavioral data (RTs: Studies I – IV; accuracy: Studies I, II, & IV; deviation from target orientation: Study IV; and post-test questionnaire: Study IV) were measured to examine how different experimental manipulations affect the performance of participants. To dive more into the neurophysiology underlying the behavioral impacts in Studies I, II and IV, scalp EEG was recorded as well.

In Studies I and II, lateralized ERP components such as the target N2pc, the distractor N2pc, the early Pd and the late Pd were extracted to examine attentional deployment to or attentional selection/suppression of lateral singletons. The N2pc onset latency was also used to examine whether attentional deployment to the target was delayed. Importantly, in Study I, the power of pre-stimulus oscillations was extracted to quantify proactive preparation when participants could predict the upcoming task. In Study IV, post-stimulus lateralized EEG power in different frequencies was calculated to examine whether the partner target and the non-relevant distractor were handled differently.

1.4.1 Study I: Selection history and proactive preparation

Study I investigated how top-down mechanisms and proactive preparation interplay with the effects of previous experience in shaping attentional control. As mentioned earlier, providing participants with the foreknowledge about the upcoming trial using a cue or sequence (Kadel et al., 2017, exp. 1 and 2) or using voluntary selection of the next task (Henare et al., 2020) cannot negate attentional biases induced by previous experience. However, there are still unanswered aspects about mechanisms underlying the proactive preparation, e.g., how learnings from the previous experience impact proactive preparation. Study I was designed to fill this gap in the literature.

To further examine the mechanisms underlying proactive preparation and its interaction with the effects of selection history, individual previous experiences and task-switching predictability were manipulated and combined in one experimental session. At the beginning of the experiment, participants were naive to their group memberships and had to learn using a trial-and-error procedure during the practice phase. Participants had to perform two tasks: the *categorization task* and the *search task*. Displays in the categorization task contained eight stimuli on an imaginary circle (Fig. 2A). All stimuli were gray circles except two, in which one deviated in color (blue or green) and the other deviated in shape (triangle or pentagon). To induce individual selection histories, participants were divided into two groups, namely the *color group* and the *shape group*. Participants in the color group had to categorize the color of the color singleton and participants in the shape group had to categorize the shape of the shape singleton. An auditory alarm was presented if participants made an error and this helped in learning their group membership. Later, the categorization task was intermingled with a search task in which all participants had to search for a diamond-shaped target and report the orientation of the embedded line (Fig. 2B). In 60% of search task trials, a red distractor was present. In distractor-present trials, the target and distractor could either be in the same hemifield or in opposite hemifields. Trials of the categorization and search tasks were intermingled either in *fixed-sequence blocks* or in *random-sequence blocks*, and the blocks were mixed and performed in one experimental session. The predictable order in the fixed sequence blocks allowed participants to proactively prepare for the upcoming task. By inducing individual selection histories and providing participants with a preparatory interval, it became possible to investigate whether and how individual selection history impacts proactive preparation. This was done by looking at the pre-stimulus alpha-band power. Subsequent effects of proactive preparation were quantified using post-stimulus ERP (the early Pd and N2pc) and behavioral measure (RTs and accuracy) to see if proactive preparation could negate attentional biases induced by selection history.

1.4.2 Study II: Selection history and predictability in attentional control

Study II built on and extended the findings of Study I and aimed at investigating the combined influence of selection history and task predictability on distractor handling when the task in always predictable, but with different levels of reliability. From the perspective of the predictive coding account and consistent with the definition of the prediction error, unexpected events activate brain responses to a larger extent compared to expected events, in order to reduce dissimilarities between the predicted model by the brain and the actual ongoing event in the real world (Summerfield, Trittschuh, Monti, Mesulam, Egner, 2008, Friston, 2009). Consistent with this idea, the presence of the distractor in an unexpected location (Heuer & Schubö, 2020; Wang et al., 2019; van Moorselaar et al., 2021) or a distractor with an unexpected feature (van Moorselaar & Slagter, 2019; Burra & Kerzel, 2013) has been shown to capture more attention than when the distractor location or feature matches the observer's expectation. The size of the prediction error depends highly on a factor, namely precision expectations or prediction reliability, that defines which unexpected signal needs to be attended in order to reduce the prediction error (Feldman & Friston, 2010). Yet, it is unclear how selection history influences the precision expectation of the target dimension and how changes in the prediction reliability influence selective control and distractor handling. Study II strives to answer these questions by manipulation of selection history and task predictability.

Manipulation of the selection history was done similar to that of Study I. Accordingly, participants were divided into the *color group* and *shape group*. Participants in both groups responded to the categorization and search tasks similar to those in Study I. However, the tasks in this study differed from the tasks in Study I in the following respects: a) a red color distractor was present in 50% of trials in the search task, b) the singletons always appeared on the horizontal or vertical meridians (Fig. 3A, B), and c) participants performed the task in two sessions. In one session, the tasks were intermingled with high predictability similar to the fixed-sequence blocks in study I (*high-predictable trial sequence*; Fig. 3C, upper panel). In another session, tasks were intermingled with low predictability (*low-predictable trial sequence*; Fig. 3C, lower panel) in a sequence of variable likelihoods as follows: While the second trial was a 100% repetition from the first trial, the third trial could be either a switch or repetition with the same likelihood of 50%. The fourth trial could be either a switch or repetition if the three preceding trials were the same. But it could be 100% repetition trial if the third trial was a switch. By locating the distractor on the meridians, it was possible to isolate the distractor processing from the target processing (Hickey et al., 2009; Wang et al., 2019). That is, the lateralized ERP could be attributed to the singleton on the horizontal meridian. By dividing the experiment into two sessions with different levels of predictability, participants were more incentivized to adopt a preparatory strategy in high-predictable trial sequences because they would know that their strategy can be used for the entire session and not just in a block like that of Study I. Influences of task predictability and selection history on distractor handling was quantified by means of behavioral measure (RTs and accuracy) and post-stimulus lateralized ERP. When the target is laterally presented, its selection would be reflected in an N2pc component. When the distractor is laterally presented, it is expected to be suppressed and this should be reflected in the early Pd (for proactive distractor suppression) and the late Pd (for reactive distractor suppression) components. However, the salient distractor might capture attention which would be reflected in the distractor N2pc.

1.4.3 Study III: A model for selection history

The aim of Study III was to propose an algorithmic-level model to computationally describe the interplay between physical salience, observer's goal, and history of previous experience in guiding visual attention to a target in a search array.

In order to include bottom-up effects in the suggested model, color map, shape map, and orientation map were extracted and combined to constitute a saliency map. A history map was also extracted and together with the saliency map was fed into the integrated priority map. The history map and saliency maps were weighted and integrated, and these weights formed the model for the top-down influences. When constituting the history map, it was considered whether learning from previous experience shaped based on the dimensional level (color vs. shape) or based on the featural level (e.g., triangle or pentagon). The outputs of the model were predictions on the parameter of reaction time distribution and weights for the history map and saliency maps. The predicted parameters of reaction time distribution were fitted to the reaction time data set of Feldmann-Wüstefeld et al. (2015, exp. 1). Experiment 1 of Feldmann-Wüstefeld et al. (2015) used the same task as that in Study I of the present dissertation with the following exceptions: The red distractor was present on 50% of the trials in the search task and the categorization and search tasks were always intermingled in a random order.

In sum, Study III aimed to introduce an algorithmic-level model to describe how learning from previous experience competes with the influences of bottom-up and top-down control mechanisms in allocating attention to a specific target in the space.

1.4.4 Study IV: Attentional capture in joint action

Study IV looked at the deployment of attention when an agent performed a *joint action* visual search task alongside a partner in different social contexts (cooperation and competition). Previous studies have shown that, when sharing a task with a partner, the agents process their partner target in a functionally similar way as their own target (Sebanz et al., 2003) and different from the non-relevant distractor (Atmaca et al., 2011, Saunders et al., 2019) although both the partner target and non-relevant distractor are non-target for the agent. As a result, representation of the partner's action interferes with the agent's own action and this impairs the agent's task performance. Furthermore, previous studies have generally shown that the influence of the partner target on the agent's performance is more pronounced in cooperative than in competitive condition (Ruissen & de Bruijn, 2016; Mendl et al., 2018; but see Ruys & Aarts, 2010). Study IV aimed at looking at the neurophysiological processes underlying processing of the partner target in different social contexts.

Two participants were sitting side-by-side and responding to a variation of the additional singleton paradigm. EEG data were recorded from one participant (*the agent*) while no EEG data were measured from the other participant (*the partner*; Fig. 5A). Search display in each trial contained two color stimuli (the agent target and the partner target, the agent target and a non-relevant distractor, the partner target and the non-relevant distractor, or two non-relevant distractors). One colored stimulus was presented on the vertical meridian and the other was presented on the horizontal meridian. This design of the stimuli helped to filter the effect of the item on the vertical meridian on the lateralized EEG, and if there is any, the post-stimulus lateralized alpha-band modulation can be attributed to the stimulus on the horizontal meridian. Importantly, each pair of participants performed the task in two sessions, one in the cooperative context and the other in the competitive context. This design made it feasible to quantify attentional deployment to or attention suppression of the partner target depending on the social context. In addition to the EEG, behavioral data (RT, accuracy, and deviation from target orientation) from the agents were recorded and analyzed.

2 STUDY SUMMARIES

This chapter starts with an overview of four studies involved in the present dissertation (Fig. 1). The background, research questions, and main measures of every individual study are presented. Later on, each study is summarized and graphical presentations are used for further clarifications.

Studies	*Background*	*Research questions*	*Main measures / method*
Study I	*Proactive preparation fails to negate attentional biases induced by selection history.*	*How do the influences of proactive preparation and selection history on attentional control are combined?*	*ERPs (N2pc, early Pd, N2pc onset latency), pre-stimulus alpha-band oscillations, response times, & accuracy*
Study II	*According to the predictive coding account, unexpected stimuli evoke larger brain responses than expected stimuli. Thus, a surprising distractor should capture more attention than a predictable distractor.*	*What is the combined influence of selection history and task predictability on distractor attentional capture and precision expectation of the target feature?*	*ERPs (N2pc, early and late Pd, onset latency), response times, & accuracy*
Study III	*Bottom-up, top-down, and selection history compete to guide attention in a winner-take-all manner.*	*What are the computations underlying the contribution of selection history in the integrated priority map?*	*Response times & algorithmic-level modeling*
Study IV	*When sharing a task, participants represent their partner's action and integrate it into their own action depending on the social context.*	*How do people process the partner target compared to the non-relevant distractors? What is the role of social context?*	*Lateralized EEG oscillations, response times, accuracy, deviation from target orientation, & post-test questionnaire*

Figure 1. An overview of the background, research questions, and methods used in the studies involved in the present dissertation.

2.1 Study I: Selection history and proactive preparation

Reference

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology, 59*(4), e13987. https://doi.org/10.1111/psyp.13987

(Find the original manuscript here: page 70 – 88)

Summary

As studies on associative learning have suggested, experience with a specific stimulus dimension as a predictor biases visual attention toward the selection of the stimulus in that dimension, even when predictiveness is removed (e.g., Feldmann-Wüstefeld et al., 2015). Predictability about the upcoming task, on the other hand, facilitates selective attention by engaging proactive reconfiguration of the task sets (Monsell & Mizon, 2006; Braver, 2012). Recent studies have shown that the residual effects of previous experience persist and continue biasing visual attention even when predictability about the upcoming task facilitates proactive preparation (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Henare et al., 2020). Yet, the question that has not been addressed is that how strategic task preparation interplay with selection history effects when performing a visual search task. What are the neurophysiological correlates of proactive preparation and how does selection history affect them? Study I used different measures (RT, accuracy, ERP, and alpha-band oscillations) to answer these questions.

In study I, participants responded to a mixture of two tasks, namely the categorization and the search task. The categorization task was an array of eight objects from which six were gray circles, one was a circular color singleton (blue or green) and the other was a gray shape singleton (triangle or pentagon; Fig. 2A). Participants in the color group had to categorize the color of the color singleton and participants in the shape group had to categorize the shape of the shape singleton. In the search task, participants from both groups had to search for a diamond-shaped target and report the orientation of the embedded line (horizontal or vertical) while ignoring the red distractor presented in 60% of trials (Fig. 2B). Based on the literature, the color distractor was expected to capture more attention from the color group participants than from the shape group participants, referred to as the selection history effect (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017). To examine the impact of proactive preparation on selection history effects, the categorization and search tasks were intermingled in fixed-sequence and random-sequence blocks.

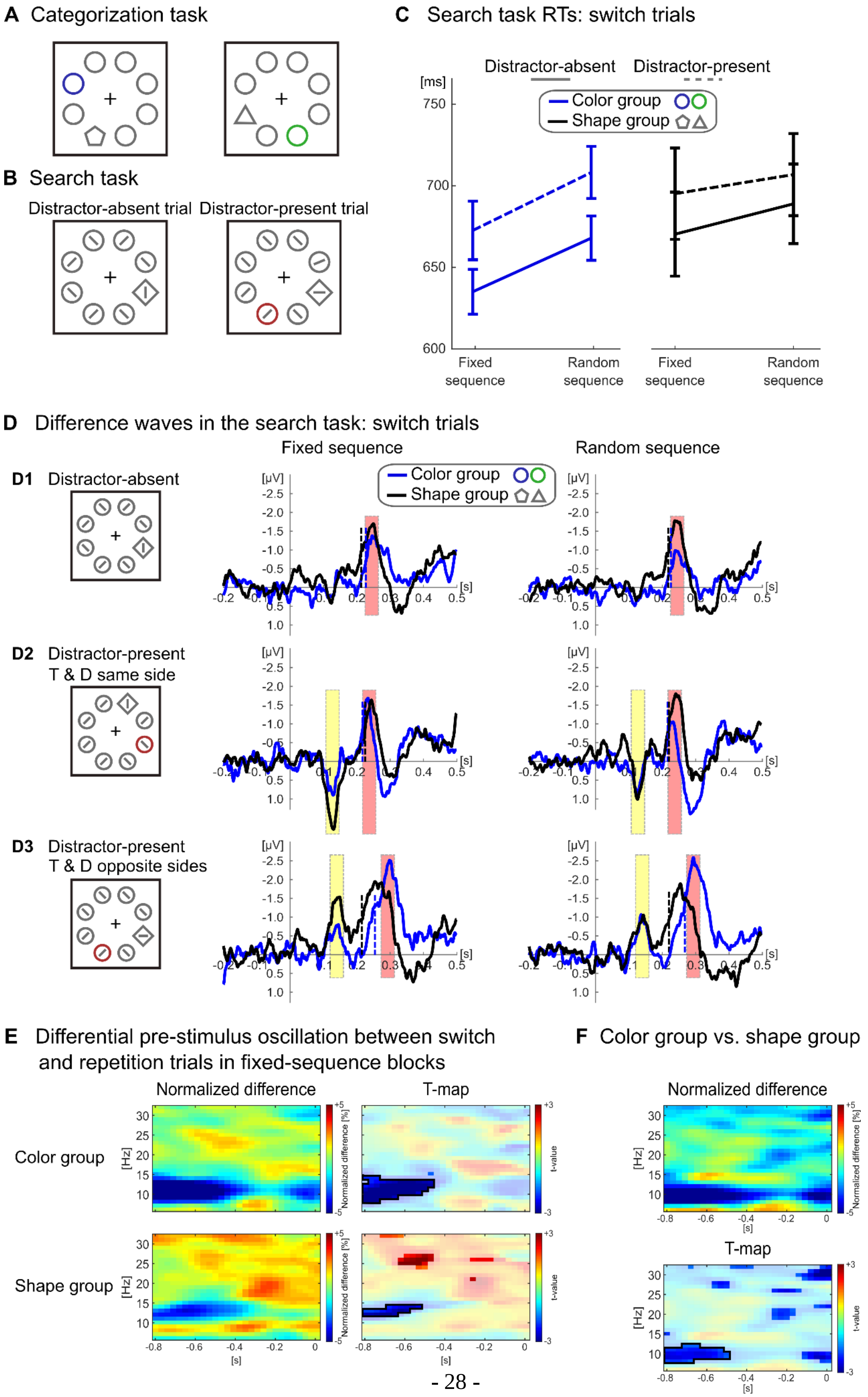

A Categorization task
B Search task
Distractor-absent trial
Distractor-present trial
C Search task RTs: switch trials
Distractor-absent
Distractor-present
Color group
Shape group
[ms]
750
700
650
600
Fixed sequence
Random sequence
Fixed sequence
Random sequence
D Difference waves in the search task: switch trials
Fixed sequence
Random sequence
D1 Distractor-absent
D2 Distractor-present
T & D same side
D3 Distractor-present
T & D opposite sides
Color group
Shape group
[μV]
-2.5
-2.0
-1.5
-1.0
-0.5
0.5
1.0
-0.2
-0.1
0.1
0.2
0.3
0.4
0.5
[s]
E Differential pre-stimulus oscillation between switch and repetition trials in fixed-sequence blocks
Normalized difference
T-map
Color group
Shape group
[Hz]
30
25
20
15
10
-0.8
-0.6
-0.4
-0.2
0
[s]
+5
-5
Normalized difference [%]
+3
-3
t-value
F Color group vs. shape group
Normalized difference
T-map

Figure 2. (A & B) Exemplary displays of the categorization and the search tasks. In the categorization task (A), participants in the color group had to report the color of the color singleton, and participants in the shape group had to report the shape of the shape singleton. At the beginning of the experiments, participants were naïve to their group membership, and they had to find out by trial and error. After each error, auditory feedback was presented. In the search task (B) all participants had to report the orientation (horizontal vs. vertical) of the line embedded inside the diamond-shaped target. A colored distractor was present in 60% of trials (right panel). **(C)** Reaction times in switch trials in the search task for participants in the color (blue) and the shape (black) groups when the color distractor was absent (solid lines) or present (dashed line), separately for fixed-sequence and random-sequence blocks. Error bars show standard error of the means. **(D)** Lateralized ERP in the search task in distractor-absent (D1) and distractor-present trials when the target and distractor were on the same side (D2) or on the opposite sides (D3) in the color (blue lines) and the shape (black lines) groups. ERPs are time-locked to the stimulus onset and averaged over PO7 and PO8 electrodes. Vertical dotted lines depict the N2pc onset latencies. For illustration purposes, the waveforms were low-pass filtered at 35 Hz (12 dB/oct). **(E)** Pre-stimulus oscillation in fixed-sequence blocks at 17 posterior electrodes (averaged across O1/2, PO7/8, PO3/4, P7/8, P5/6, P3/4, P1/2, Oz, POz, and Pz). The left panels represent normalized differences between power spectrums in switch and in repetition trials in the search task calculated as [(switch - repetition) / (switch + repetition)]×100 in the frequency range of 6 – 32 Hz and time range of -800 – 0 ms time-locked to the stimulus onset. The right panels represent t-values resulted from the within-subject comparison between switch and repetition trials using the dependent-sample t-test by cluster-based permutation test. The opacity of the non-significant bins ($p > .01$) was reduced by 80%. **(F)** The upper panel depicts the between-group comparison of the normalized switch-vs-repetition powers over 17 posterior channels. The lower panel depicts the t-values calculated from the independent t-test by cluster-based permutation test. The opacity of the non-significant bins ($p > .05$) was reduced by 80%.

Participants in the shape group could establish one attentional set for both categorization and search tasks. They were always selecting the shape singleton and ignoring the color distractor. Participants in the color group, however, needed to change between two different attentional sets when switching between the tasks: While color was the response-relevant dimension and shape was the response-irrelevant dimension in the categorization task, these roles swapped in the search task. Because of these between-group differences in reconfiguration processes, proactive task-set reconfiguration and its behavioral/electrophysiological correlates in fixed-sequence blocks were expected to be more pronounced in the color-categorization than in the shape group.

As expected, in fixed-sequence blocks and in both groups, pre-stimulus posterior alpha-band power in switch trials reduced when compared to repetition trials (Fig. 2E). Critically this difference was more pronounced in the color group than in the shape group (Fig. 2F). This differential pre-stimulus alpha-band modulation indicated stronger proactive preparation in the color group than in the shape group. Subsequently, stronger proactive preparation in the color group was reflected in RT and ERP results. Participants in the color group showed a larger reduction of behavioral distractor cost (Fig. 2C) in fixed-sequence than in random-sequence blocks compared to participants in the shape group. These results suggest that stronger proactive preparation resulted in more focused attentional deployment and better task performance. Strikingly, in fixed-sequence blocks, the early Pd component revealed a larger amplitude in the shape group than in the color group (Fig. 2D, middle and last rows). This indicated that those participants who exerted less pre-stimulus proactive preparation (e.g., shape group) needed to put a strong effort in early distractor suppression after stimulus onset, while those participants who put more effort in pre-stimulus proactive preparation (e.g., color group) needed less early distractor suppression. Despite all these evidence of strong proactive preparation in the color group, participants in this group revealed larger distractor cost and more delayed N2pc onset latency when compared to the shape group, even in fixed-sequence blocks. This indicates that despite the strong task preparation in the predictable fixed sequence blocks, the color distractor captured more attention from the color group than from the shape group.

In sum, Study I showed that participants utilize advance preparation when it is possible to proactively prepare for the upcoming task. This proactive preparation enhances participant’s task performance, especially in those participants who need stronger task-set reconfiguration. However, the results of this study provided strong evidence for the notion that proactive top-down control doesn’t have the potency to negate the residual effects of selection history.

2.2 Study II: Selection history and predictability in attentional control

Reference

Abbasi, H., Henare, D., Kadel, H., & Schubö, A. (2023). Selection history and task predictability determine the precision expectations in attentional control. *Psychophysiology*, e14151.https://doi.org/10.1111/psyp.14151

(Find the original manuscript here: page 89 – 103)

Summary

Predictive coding framework suggests that the brain is not a passive system which only processes the sensory input from the environment, but it also builds and test predictive models to optimize its interaction with the environment (Friston, 2009; Feldman & Friston, 2010). The brain prioritizes processing of the unexpected stimuli to reduce the mismatch between its prediction from an event and the actual event (Summerfield et al., 2008). Previous studies have proven incorporation of both physical salience (Baldi & Itti, 2010) and top-down predictions (Noonan et al., 2016) in predictive coding framework. That is, when the presence of the distractor in a specific location is expected, brain response to the distractor is suppressed (Wang et al., 2019; van Moorselaar & Slagter, 2019). However, considering the central role of selection history in attentional control (Awh et al., 2012; Feldmann-Wüstefeld et al., 2015), it is not clear how selection history and predictive coding are integrated. Study II is conducted to fill this gap by manipulation of individual selection history and task predictability. The most important goals of Study II are to examine the impact of selection history on the precision expectation of the target dimension, and the extent to which task predictability facilitates selective processes and distractor handling.

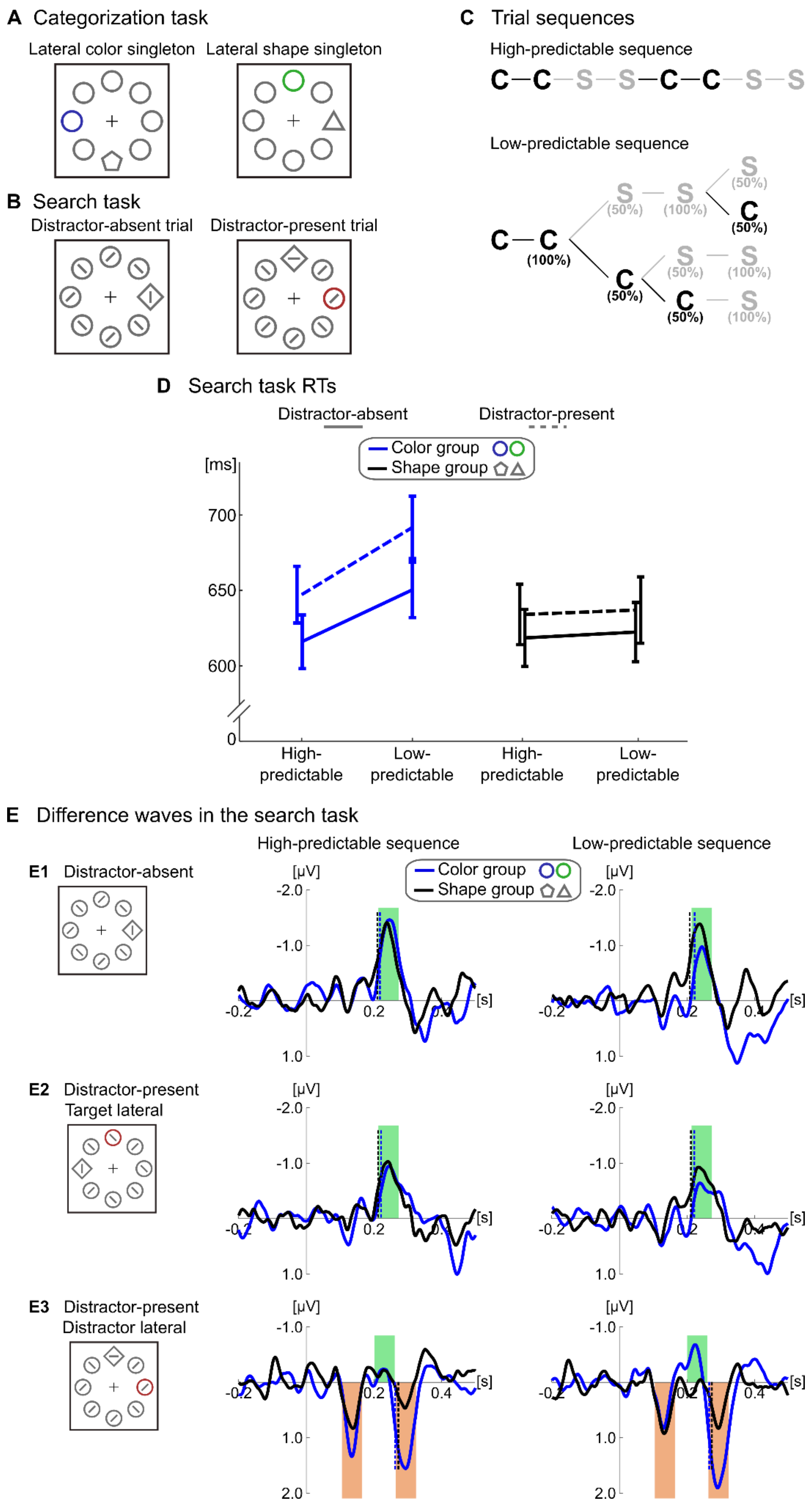

A Categorization task
Lateral color singleton
Lateral shape singleton
B Search task
Distractor-absent trial
Distractor-present trial
C Trial sequences
High-predictable sequence
C—C—S—S—C—C—S—S
Low-predictable sequence
C—C (100%)
S (50%) — S (100%)
S (50%)
C (50%)
C (50%)
S (50%) — S (100%)
C (50%) — S (100%)
D Search task RTs
Distractor-absent
Distractor-present
Color group
Shape group
[ms]
700
650
600
0
High-predictable
Low-predictable
High-predictable
Low-predictable
E Difference waves in the search task
High-predictable sequence
Low-predictable sequence
E1 Distractor-absent
E2 Distractor-present Target lateral
E3 Distractor-present Distractor lateral
Color group
Shape group
[μV]
-2.0
-1.0
1.0
2.0
-0.2
0.2
0.4
[s]

Figure 3. (A & B) Exemplary displays of the categorization and search tasks. The categorization task, search task, and learning phase were similar to those in Study I. Dissimilar to that in Study I, in Study II a lateralized arrangement of the stimuli was used in which the singletons always appeared on the meridian axes. Furthermore, 50% of the search task trials contained a color distractor. **(C)** Depiction of trial sequences in high-predictable (upper panel) and low-predictable (lower panel) trial sequences. "C" stands for the categorization task and 'S' stands for the search task. In high-predictable trial sequence, the tasks repeat after a switch. Number in the parentheses show the likelihood of a trial in low-predictable trial sequence. Based on a pre-defined logic, sometimes tasks switch/repeat with the likelihood of 100% while sometimes the likelihood of task switch/repetition is in the chance level. Each participant completed 25 blocks, each block 64 trials, in each level of predictability is two separate sessions. **(D)** Reaction times in the search task for participants in the color (blue) and the shape (black) groups when the color distractor was absent (solid lines) or present (dashed line), separately for high-predictable and low-predictable trial sequences. Error bars show the standard errors of the means. **(E)** Lateralized ERP in the search task in distractor-absent (E1) and distractor-present trials with the lateralized target (E2) or with the lateralized distractor (E3) in the color (blue lines) and the shape (black lines) group. ERPs are time-locked to the stimulus onset and averaged over PO7/8, PO3/4, and P7/8 electrodes. Vertical dotted lines depict the onset latencies. For illustration purposes, the waveforms were low-pass filtered at 35 Hz (zero-phase, Butterworth, order two).

Manipulation of the individual selection history was done similarly to that of Study I. That is, via a categorization task (Fig. 3A), participants learned to categorize either the color of the color singleton (color group) or the shape of the shape singleton (shape group). Later, the categorization task was intermingled with a search task in which all participants had to search for a diamond-shaped target and report the orientation of the embedded line (horizontal or vertical) while ignoring the red distractor presented in 50% of trials (Fig. 3B). Crucially the experiment was done in two sessions with different levels of task predictability while scalp EEG data were recorded. In one session participants could predict the next trial with 100% certainty (high-predictable trial sequence; Fig. 3C, upper panel), while the task predictability was reduced in another session (low-predictable trial sequence; Fig. 3C, lower panel). In low predictable trial sequence, participants in the shape group were expected to incorporate their individual selection history and top-down information to tune the prediction reliability about their target dimension as they always searched for a shape singleton. However, for the color group, selection history couldn't contribute in tuning the prediction reliability about the target dimension as experience in the color dimension would be detrimental when doing a search task. By increasing the task predictability, participants in the color group had the chance to utilize the prediction about the next trial and optimize their prediction reliability about the upcoming target. The impact of task predictability would be smaller for the shape group as they were always aware of their target dimension.

ERP results in the search task showed strong attentional capture by the color distractor from participants in the color group in low-predictable sequence trials as reflected in the distractor N2pc. This component was eliminated in high-predictable trial sequence where the predictability enhanced the early Pd amplitude (Fig. 3E, panel E3) and reduced behavioral distractor costs (Fig. 3D). The result suggests that increased predictability for the color group enhanced early distractor suppression and reduced the distractor attention capture by engaging proactive preparation. Besides this, participants in the color group showed a trend towards an enhanced target N2pc in high-predictable than in low-predictable trial sequences (Fig. 3E, panel E1). No such effects of predictability were observed in the shape group. Increasing task predictability caused reduction of the late Pd amplitude to the same extent in both groups, probably because of the reduced prediction error for all participants and less need for reactive suppression of the distractor in both groups in high-predictable than in low-predictable trial sequences. This suggests that participants from both groups benefited from the task predictability to the same extent to reactively suppress the color distractor, although reactive suppression was always stronger in the color than in the shape group.

In sum, Study II strived to investigate the influence of prediction reliability and selection history on selective control and distractor suppression. The results suggest that task predictability can be used to proactively suppress the distractor and it is mainly exerted when participants are incentivized. Further, as Study II showed, precision expectation of the target remained high for the shape group in all conditions because the target dimension was the same between the task, but it reduced in low-predictable trial sequence for the color group participants who had to update their target template when switching between tasks. This implies that precision expectation doesn't only depend on top-down control, but it also depends highly on selection history.

2.3 Study III: A model for selection history

Reference

Meibodi, N., Abbasi, H., Schubö, A., & Endres, D. M. (2021). A model of selection history in visual attention. *In Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 43, No. 43)

(Find the original manuscript here: page 104 – 112)

Summary

As it was laid out in Studies I and II, selection history is the third control mechanism that influences visual attention differently from bottom-up and top-down control mechanisms (for a review see Awh et al., 2012). Previous studies have proposed theoretical and computation models for bottom-up (Itti et al., 1998) and top-down control mechanisms (Borji, Sihite, & Itti, 2013) or their combination (Peters & Itti, 2007). However, selection history has not been modeled so far. The aim of Study III was to introduce a model to computationally describe how selection history competes with other control mechanisms to control visual attention. The proposed model was trained on the reaction time data from Feldmann-Wüstefeld et al. (2015, exp. 1). Similar to Study I of the present dissertation, individual selection history in Feldmann-Wüstefeld et al. (2015, exp. 1) was induced using the categorization task (Fig. 4A). The categorization task was then randomly intermingled with the search task (Fig. 4B). A red distractor was present in half of the trials in the search task. The results of Feldmann-Wüstefeld et al. (2015, exp. 1) showed a larger distractor cost in participants in the color than in the shape group. As Feldmann-Wüstefeld et al. (2015) concluded, the color distractor in the search task captures attention more from participants who had experienced color as the task-relevant dimension compared to participants who had experienced shape as the task-relevant dimension.

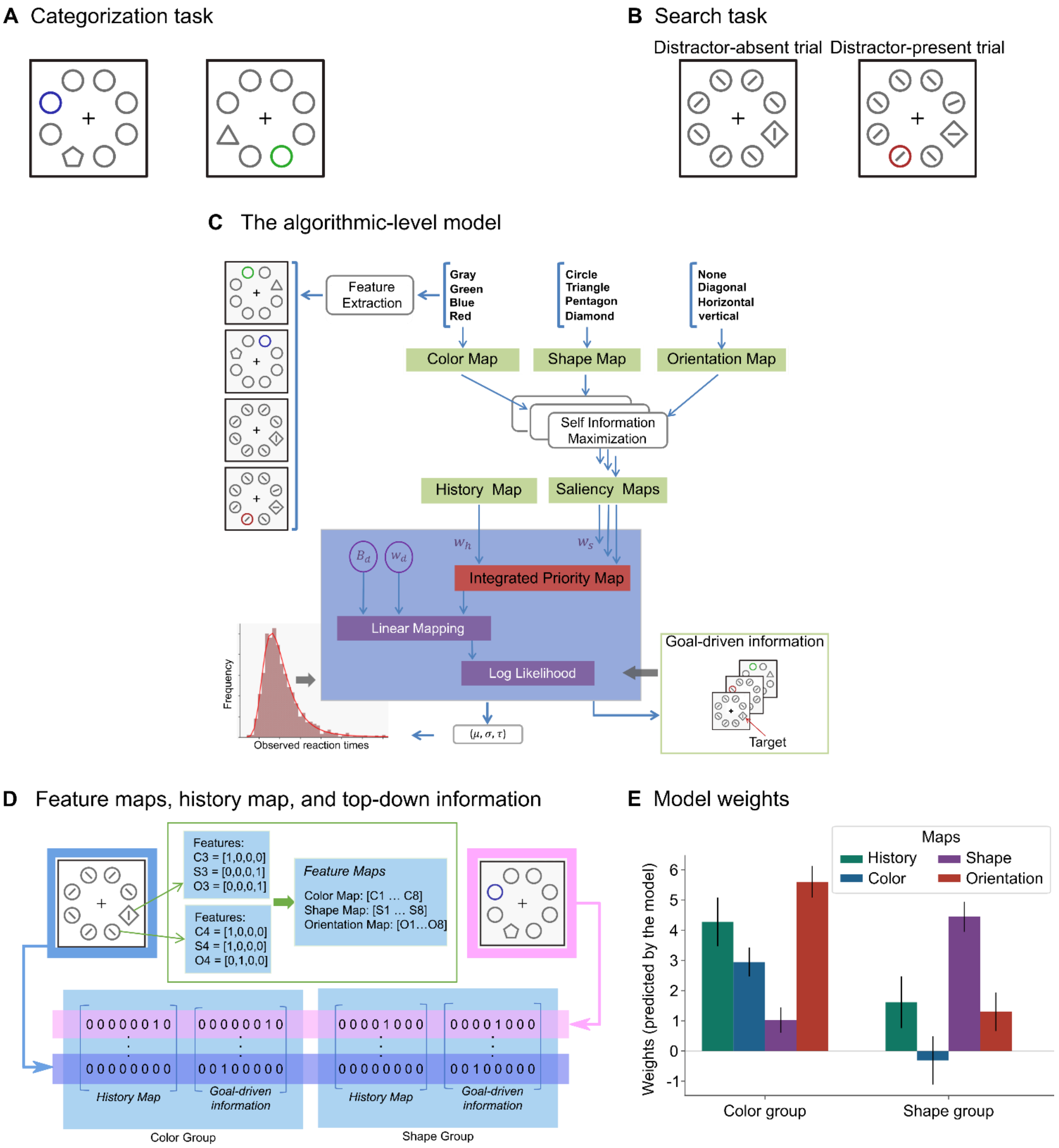


Figure 4. (A & B) Exemplary displays of the categorization and the search tasks. **(C)** An overview of the algorithmic-level model. W_s, W_h, and W_d are the weights for the saliency maps, the history map, and distribution parameters, respectively. W_s consists of three elements describing weights of the color map, shape map, and orientation map. W_d contains the predicted parameters of the ex-Gaussian distribution (μ, σ, τ). B_d stands for distribution parameters biases (B_μ, B_σ, B_τ). Blue arrows depict the direction of data flow and gray arrows depict the direction of feedback. **(D)** This panel shows the feature maps, the history map and the top-down map for two different trials. Feature vectors for each stimulus on the screen were created using 1-out-of-K encoding, where K stands for the number of feature values in each dimension (K = 4). Feature maps were created by combining the color map, shape map, and orientation map across all the

stimuli on the display. This resulted in vectors with the size of 8×4. In the history map, the location of the feature associated with the learning history is marked using 'one'. In the map of the goal-driven information, the location of the task-relevant stimulus is marked using 'one'. **(E)** The map weights for the optimal model for the color (left columns) and the shape (right columns) group. Error bars show standard error of the means.

Study III introduced an algorithmic-level model to computationally describe how the observer's goal, physical salience, and effects of learning from previous episodes compete with each other to direct attention to a target, for instance in a scenario described in Feldmann-Wüstefeld et al. (2015, exp. 1). According to the feature integration theory (Treisman & Gelade, 1980), the model extracted three different features (color, shape, and orientation) from which salience maps were calculated using Attention based on Information Maximization (AIM, Bruce & Tsotos, 2009), see Fig. 4C. A history map was also created based on the elements on the display and their relations with the individual selection history of each participant (Fig. 4D). Next, integration of history map and saliency maps were controlled using weights which could be modified in each iteration of the model calculations to end up with the best fit between the output of the model which are the ex-Gaussian distribution parameters and the reaction times distribution in Feldmann-Wüstefeld et al. (2015). Importantly, three different versions of the model were tested. In version one, only predictive features in the categorization task were involved in the history map (i.e., blue and green for the color group; triangle and pentagon for the shape group). The model comparison confirmed this version to be the optimal model. In the second version, all color singletons (blue, green, and red) and shape singletons (triangle, pentagon, and diamond) were included in the history map of the color group and the shape group, respectively. In the third version, selection history map was excluded from the model.

According to the outputs of the optimal model (Fig. 4E), the history map gained a higher weight and the shape map gained a lower weight in the color group model than in the shape group model. These differences explain that participants in the color group relied on the predictive features (i.e., blue and green) to respond to the categorization task, while participants in the shape group relied mainly on the shape map because they could respond to both tasks by adopting a shape-singleton search template. Although for the color group, the features in the history map existed in the color map, the color group model relied less on the color than on the history map, because the color map contained the feature of the distractor in the search task (red). The orientation map in the search task gained the highest weight in the color group model. This shows that, instead of searching for the shape singleton, the color group model searched for the orientation singleton which didn't need to be down-weighted when switching to the categorization task. Finally, the color map gained a higher weight in the color group model than in the shape group model. This implies that the red color which existed in the color map, together with the blue and green colors, gained a higher weight in the color group model than in the shape group model. Higher weight of the color map in the color group than in the shape group support the notion that the attentional capture by the color singleton in stronger in the color group than in the shape group (Feldmann-Wüstefeld et al., 2015).

In sum, Study III introduced a model to describe how influences of selection history, top-down, and bottom-up mechanisms compete with each other in the integrated priority map to direct attention to the target. The model could correctly predict the parameters of RT distribution of the experimental measures and could also explain the attentional biased induced by individual selection history.

2.4 Study IV: Attentional capture in joint action

Reference

Abbasi, H., Dötsch, D., & Schubö, A. (submitted). I see what you see: EEG correlates of attentional capture by a partner target in joint action.

(Find the original manuscript here: page 113 – 139)

Summary

Previous studies have suggested that when people share a task in a joint action setting, they constitute a cognitive representation of their partner's action. The partner's action representation interferes with one's own action and results in a longer reaction time (Sebanz et al., 2003). Contrary to the partner target, a non-relevant distractor does not cause such interference, implying differential processing mechanisms despite both being target-irrelevant for the agent (Atmaca et al., 2011; Saunders et al., 2019). Other studies extended this and claimed that social context, such as cooperation and competition, influences the degree to which people represent their partner's action (Ruissen, & de Bruijn, 2016; Mendl et al., 2018). Previous studies have often focused on the partner's action representation. However, the joint attention and its neurophysiological correlations in different social contexts have not been fully investigated. The aim of Study IV is to investigate mechanisms involved in processing of the partner target in different social contexts using behavioral and electrophysiological measures.

In this study, pairs of participants were sitting side-by-side and searched for distinct colored targets in a joint variant of the additional singleton paradigm while one participant's (i.e., the agent) EEG and behavioral data were recorded (Fig. 5A). The visual search task consisted of eight Gabor patches arranged equidistant on an imaginary circle. One of the stimuli on the vertical meridian and one on the horizontal meridian were always color singletons and the other items were gray. One color was associated with the agent target, one with the partner target, and two were non-relevant distractors (Fig. 5B). Participants had to search for the Gabor patch in their color and report its orientation using a mouse click in the response display (Fig. 5C). If one's target was not present, they needed to click on the "No target" button. Participants performed the task in cooperative and competitive sessions. Importantly, all color singleton in the experiment had similar luminance, and thus, were of similar visual salience. Therefore, the differential attentional deployment to the partner target and the non-relevant distractors could not be the result of the difference between physical distracting potentials, but it was attributed to higher priority to the partner target than to the non-relevant distractor. The core hypothesis was that the agents would deploy more attention the partner target than to the non-relevant distractor due to the higher social value of the partner target. As a consequence, attentional capture by the partner target was expected to result in slower task performance and reduced power of alpha-band at parieto-occipital sites contralateral to the partner target's location. Previous studies on joint attention have suggested reduced alpha-band power as a marker for attentional processing of the shared target or of the partner's gaze (Lachat et al., 2012). Moreover, the agents were expected to deploy attention to the partner target in the cooperative and suppress it in the competitive condition. Based on this, the partner target would elicit a negative lateralization of alpha-band power in the cooperative condition and positive lateralization of alpha-band power in the competitive condition.

The results showed that the presence of the partner target slowed down the agent's performance, especially when the agent target was absent (Fig. 5D). This suggests attentional capture by the partner target when the agent target was absent. Attentional capture by the agent target was further confirmed using the pattern of lateralized alpha-band. Lateral presentation of the partner target generally elicited negative lateralization of alpha-band power (Fig. 5E, panel E1). This was especially the case when the agent target was absent and the partner target seemed to be the strongest stimulus to capture the agent's spatial attention (Fig. 5E, panel E3). The non-relevant distractor, on the other hand, triggered positive lateralization of alpha-band power demonstrating attentional suppression of the non-relevant distractor (Fig. 5E). Strikingly, the social context affected attentional deployment to the partner target (Fig. 5F). The partner target elicited a negative lateralization of alpha-band power in the cooperative condition, but a positive lateralization of alpha-band power in the competitive condition. This suggests attentional capture by the partner target in the cooperative condition and its suppression in the competitive condition. The suppression of the partner target by the agent in the competitive condition fits the strategy that, when competing, suppression of any non-target stimuli helps in better task performance.

In sum, Study IV provided evidence for the idea that people process their partner target in a functionally similar way to their own target and different from non-relevant distractors. This is interesting because both the partner target and the non-relevant distractors are target-irrelevant for the agent, but they seem to bear different levels of priority for the agent. Critically, the social context appeared to be a determinant factor defining when to deploy or not to deploy attention to the partner target.

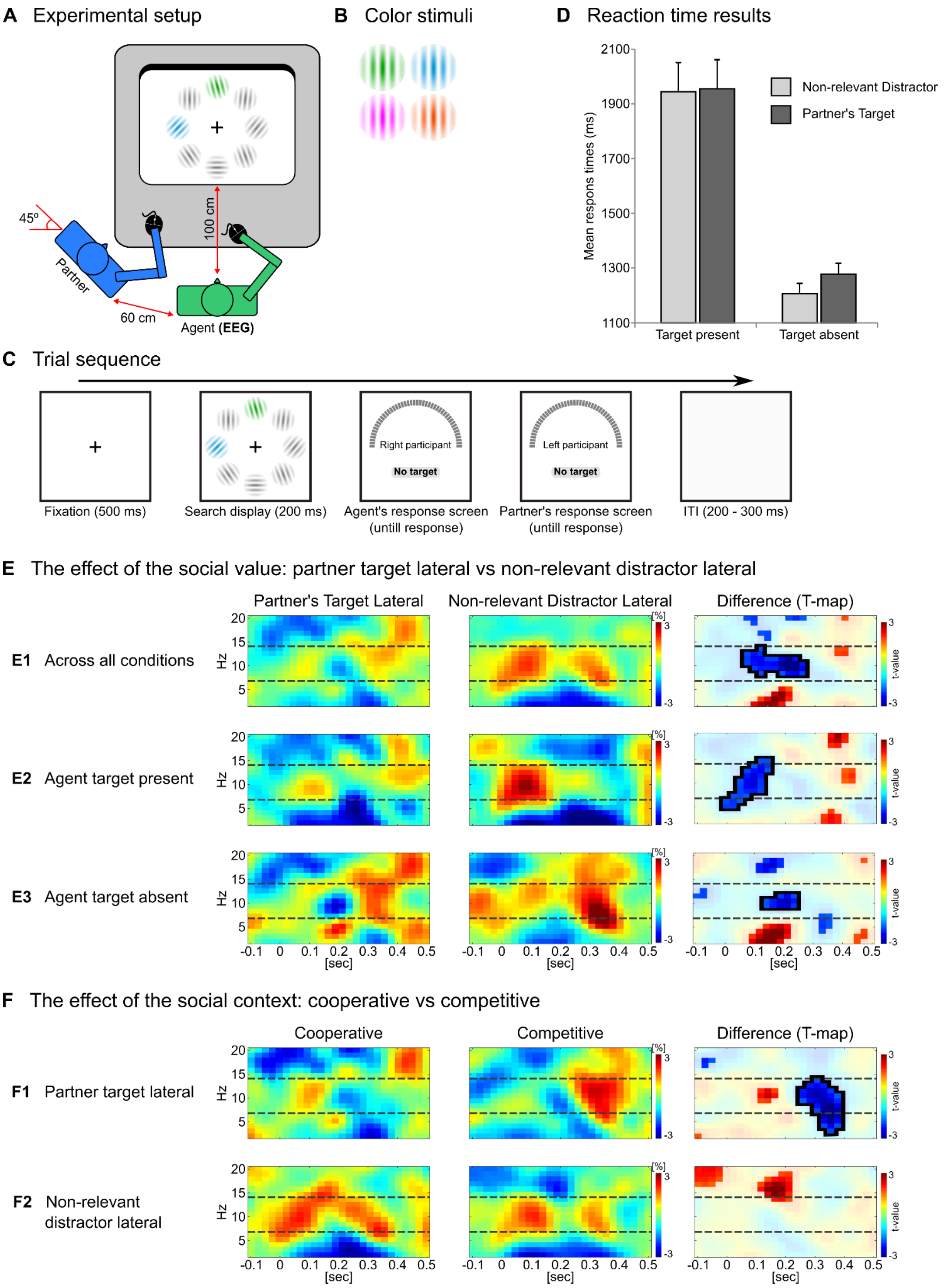


Figure 5. (A) Schematic depiction of the experimental setup: EEG was recorded from the agents while they were sitting in front of the display alongside the partner. The search display contained eight Gabor patches in which two were color singletons. In all trials, one singleton was placed on the vertical meridian while the other appeared on the horizontal meridian. **(B)** Four colors were used for color singletons: blue, green, orange, and purple. The assignments of the colors to the roles of the stimuli (the agent's target, the partner's target, and the non-relevant distractors) were counterbalanced. All color stimuli were of equal luminance. **(C)** Trial procedure: First, the agents had to report the orientation of their target using a mouse click. Next, the partners had to report their target orientation. Participants had to click on the "No target" button if their targets were not present. **(D)** Reaction time results: The two left columns depict the agents' mean RTs when their targets were present. The two right columns depict the agents' mean RTs when their targets were absent. Dark gray

represents trials containing the partner target and light gray represents trials without the partner target. Error bars show the standard error of the means. **(E & F)** Lateralized oscillatory power calculated as [(contralateral - ipsilateral) / (contralateral + ipsilateral)]×100. **(E)** The effect of the social value: Lateralized oscillatory power across all conditions (E1), when the agent target was present (E2), and when the agent target was absent (E3) averaged over PO7/8, PO3/4, and P7/8 electrodes. The left panels represent the lateralization indices elicited by the partner target, and the middle panels represent the lateralization indices elicited by the non-relevant distractors. The right panels represent t-values resulted from comparing lateralization indices using a cluster-based permutation test. **(F)** The effect of the social context: Lateralized oscillatory power for elicited by a laterally presented partner target (F1) and a laterally presented non-relevant distractor (F2) in cooperative (left panels) and competitive (middle panels) conditions. The right panels represent t-values resulted from comparing lateralization indices using a cluster-based permutation test. In panels E and F, the opacity of the non-significant bins ($p > .05$) was reduced by 80%.

3 GENERAL DISCUSSION

In four studies, the current dissertation strived to examine the influence of a wide range of factors such as selection history, task predictability, social value and social context on attentional control. The studies in this dissertation can be divided into two main parts. The first part which includes Studies I-III examines the influence of the selection history (Awh et al., 2012) on selective attention. Strikingly, the first two studies examined how and whether task preparation influences attentional biases induce by selection history. Recent studies have shown a long-lasting effect of selection history on attentional selection which can be reduced by increasing task predictability, but it can’t be negated (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Henare et al., 2020). Study I investigated the combined impact of proactive preparation and selection history on attentional control from the perspective of task-set reconfiguration. Study II used a predictive coding framework to describe the combined influence of task predictability and selection history on proactive and reactive distractor suppression. Study III can be considered as a complementary study to expand the understanding of the interaction between selection history and other control mechanisms. To do so, Study III introduced an algorithmic model to quantitively describe the interaction between selection history, bottom-up and top-down mechanisms.

The second part of the current dissertation focuses on selective attention in joint action. More specifically, Study IV investigated the influence of social value and social context (Sebanz et al., 2003; Hommel et al., 2009) on selective attention or suppression of the partner target. Previous studies have used different theoretical accounts such as action co-representation (Sebanz et al., 2003; 2006), referential coding (Dolk et al., 2013; 2014) and spatial response coding (Dittrich et al., 2012; 2013) to describe the influence of the partner target on the agent’s action. Yet, the influence of the partner target on the agent’s attentional selection is not fully understood. To examine the influence of social value on attentional selection, Study IV examined whether a partner target is processed differently than a non-relevant distractor, given that both are non-target for the agent. Moreover, Study IV examined the influence of the social context (cooperative vs. competitive) on attentional selection. Previous studies have shown the impact of the partner target on the agent action is substantially larger in the cooperative than in the competitive conditions (Hommel et al., 2009; Ruissen & de Bruijn, 2016; Mendl et al., 2018). Study IV aimed to extend these findings by investigating the impact of the social context on attentional selection of the partner target.

To answer the research questions in Studies I, II and IV, behavioral and EEG data were recorded. In Study III, only the behavioral data from Feldmann-Wüstefeld et al. (2015, exp. 1) was used to test the algorithmic model of the interplay between selection history and other control mechanisms. This section (general discussion) aims to discuss the findings of studies I – IV in relation to each other and connect them to the existing literature to create a whole picture from the findings and its contribution to the current knowledge from selective attention.

To facilitate the reader's understanding from the current discussion, Fig. 6 summarizes the research questions, the main results and brief conclusions in each study.

Studies	***Research questions***	***Main results***	***Brief conclusions***
Study I	*How does the combination of proactive preparation and selection history impact attentional control? What are the EEG correlates of proactive preparation? How does selection history change these correlates?*	*Reduced alpha-band power in switch than in repetition trials, only in fixed-sequence blocks of the search task. This was more pronounced in the color than in the shape group, however, for the color group, distractor cost remained larger and the N2pc emerged later.*	*Depending on the individual selection history, participants proactively reconfigure their attentional control in predictable contexts. Proactive reconfiguration can't negate the selection history biases.*
Study II	*How selection history impacts precision expectations in predictive coding framework? How the combination of precision-weighted expectations and prediction error influences distractor handling?*	*Higher task predictability increased the early Pd and recued the distractor N2pc in the color group. In the same group, RT and the target N2pc was enhanced when task predictability increased. In the shape group, no distractor N2pc was observed and predictability didn't affect early Pd.*	*Previous experience with a dimension adjusts precision expectations of that dimension. Consequently, any stimulus in that dimension captures attention. Task predictability can only reduce this attentional capture via proactive suppression.*
Study III	*What is the computational logic behind the interaction between selection history and other control mechanisms (bottom-up and top-down)?*	*The weights of history and color maps were higher in the color than in the shape group. For the shape group, the color map gained the smallest weight while the shape map gained the largest weight.*	*The higher weight of the color map in the color than in the shape group explains why the color distractor captures more attention from the color group.*
Study IV	*Is a partner target processed different from a non-relevant distractor given that both are non-target for the agent? How is the influence of the social context and what are the EEG correlates?*	*Lateralized alpha-band power was negative for the partner target and positive for non-relevant distractor. However, lateralized alpha-band power emerged by the partner target was negative in the cooperative and positive in the competitive condition.*	*EEG findings suggest that the partner target captures attention in the cooperative condition and it is suppressed in the competitive condition. Contrary to this, the non-relevant distractor is always suppressed.*

Figure 6. An overview of the research questions, main results and the brief conclusions in each study involved in the present dissertation.

3.1 Selective attention is shaped by

3.1.1 …selection history

Recently a large body of research has suggested selection history as a third major factor which interacts with bottom-up and top-down control mechanisms to drive attention in the integrated priority map (Awh et al., 2012). Associative learning is a form of selection history and posits that previous selection of a feature dimension continues to show higher saliency as well as higher strength in attentional capture even when that feature is not target-relevant anymore (Le Pelley et al., 2011; Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017). In the first part of this dissertation (Studies I – II), to induce selection history, the same manipulation as that in Feldmann-Wüstefeld et al, 2015 was used. That is, during a categorization task, participants in the color group learned to categorize the color of the color singletons (blue vs. green) and participants in the shape group learned to categorize the shape of the shape singletons (pentagon vs. triangle). Extracting N2pc from the recorded scalp EEG made it possible to precisely track the attentional allocation on the task-relevant singletons. The N2pc component is a well-known biomarker of target selection (Eimer, 1996; Luck & Hillyard, 1994a, 1994b; Woodman & Luck, 2003) and has been shown to emerge when a salient distractor captures attention (Liesefeld et al., 2017; Berggren & Eimer, 2018).

In the categorization task in study I, when the singletons were in the same or opposite sides, the lateralized ERPs were locked to the location of the color singleton in the color group and to the location of the shape singleton in the shape group (see Fig. 3 in the original paper of study I). The N2pc results showed a pronounced N2pc amplitude in both groups, suggesting that all participants attended their task-relevant singleton. The same was observed in the categorization task in Study II: When the task-irrelevant singleton was on the vertical meridian, the lateralized color singletons elicited the N2pc in the color group and the lateralized shape singletons elicited the N2pc in the shape group (see Fig. 2d in the original paper). These observations in two experiments were already observed by earlier studies (e.g. Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017) and prove that participants learned their group membership and attended their task-relevant singletons through the experimental sessions. One basic expectation which comes from the definition of “selection history” is that selection of a feature dimension in the categorization task would result in an attentional bias toward the selection of that feature in another tasks.

To examine this basic hypothesis and measure selection history biases, in the first three studies, the categorization task was interleaved with a search task in which all participants had to report the orientation of a line (vertical vs. horizontal) embedded in a diamond shaped singleton while a color distractor was present in some trials (additional singleton paradigm; Theeuwes, 1992). In the original version of the additional singleton paradigm, the colored distractor captures attention and is generally indexed by longer RTs in distractor-present than in distractor-absent trials. The results of Studies I and II showed that the magnitude of this distractor cost highly depends on the individual selection history. That is, participants in the color group showed larger behavioral distractor cost than participants in the shape group. This finding was further confirmed by ERP results: In the search task in Study I, the presence of the color distractor on the opposite side of the target location delayed the emergence of the target N2pc in the color group. This fits well with the existing literature showing the distractor on the opposite side of the target location delays attentional selection of the target due to the filtering cost (Wykowska & Schubö, 2011; Mazza et al., 2009; Folk & Remington, 2006). That is, although the target outcompetes the distractor when competing for attention capture, this competition results in a delay in attentional selection of the target which is reflected in the delayed N2pc and longer RT. In Study I, previous experience with color singletons enhanced the saliency of the color distractor in the search task for the color group participants. This could be a reason that participants in the color group were distracted by the color singleton to a larger extent and showed a delayed target selection as compared with the participants in the shape group. In the search task in Study II, the lateralized distractor induced a distractor N2pc only in the color group when task predictability was low. This fits well with a body of literature suggesting attentional capture by the salient distractor (Berggren & Eimer, 2018; Barras & Kerzel, 2017; Liesefeld et al., 2017), especially when the feature of the upcoming target in not known (Burra & Kerzel, 2013) or when the current distractor has the dimension of the target in another task (Feldmann-Wüstefeld et al., 2015).

Therefore, the first two studies showed that distractor attentional capture doesn’t only depend on the physical salience and top-down control, but on the individual selection history of the observer. This observation was further confirmed in Study III when an algorithmic model strived to quantitively describe the contribution of selection history in attentional selection. As the model suggested, when performing a combination of the categorization and search tasks used in Studies I and II, participants in the color group relied on the history map (blue and green) because they needed that in half of the trials when responding the categorization task. This could have consequences to unintentionally increase the weight of the color map (blue, green, red) which contained the future of the color distractor. However, participants in the shape group neither relied on the color map, nor on their history map (pentagon and triangle), because they could perform both tasks by only relying on the shape map (pentagon, triangle, diamond, circle). As a consequence, the red distractor could get more salient for the color group participants and capture more attention from participants in this group.

In sum, the first part (Studies I-III) showed a persistent and strong impact of selection history on attentional selection. That is, attention is biased toward the selection of a stimulus which shares dimension with individual selection history.

3.1.2 …proactive preparation

The first two studies of this dissertation examined the effects of the proactive preparation on attentional control and distractor handling. When an observer is presented with a task, there might be several ambiguities before stimulus onset such as the presence of the target and distractor, their characteristics, effector selection and temporal characteristics of stimuli. A two-stage model suggests that, while parts of these ambiguities can be resolved before stimulus onset when the task is predictable (proactive control), there will be a residual proportion of the reconfiguration which can be resolved only after task presentation (reactive control; Rogers & Monsell, 1995; Braver, 2012; Koch et al., 2018). Importantly, proactive control mechanism has been shown to be more pronounced in switch than in repetition trials, because some task settings are already available in the repetition trials which need to be reconfigured in switch trials (Roger & Monsell, 1995; Monsell & Mizon, 2006; Vandierendonck et al., 2010).

Due to the high temporal resolution and ongoing measurements, EEG can quantify the proactive preparation even before stimulus onset. For instance, in a predictable task, proactive preparation has been reflected in the power of the pre-stimulus alpha-band oscillation (Wang et al., 2019; van Zoest et al., 2021; Noonan et al., 2016). In Study I, pre-stimulus alpha-band power in the search task was used to track proactive preparation. The search task EEG results showed a significantly reduced pre-stimulus posterior alpha-band power in switch than in repetition trials in the color group as well as in the shape group, but only when the task sequence was predictable. As a direct behavioral consequence, RTs were faster in fixed- than in random-sequence blocks. This suggests that in a predictable task sequence, proactive preparation engages before stimulus onset and to a stronger degree in switch than is repetition trials to facilitate task-set reconfiguration which results in an enhanced task performance. This fits well the existing literature which have shown reduced pre-stimulus posterior alpha-band in switch than in repetition trials (Poljac & Yeung, 2014; Cooper et al., 2016; Wolff et al., 2017; Proskovec et al., 2019). For instance, when participants were cued to either switch between the tasks or repeat the same task, a reduced posterior alpha-band power after the cue onset in switch trials suggested the involvement of rule updating and working memory (Cooper et al., 2016). Contrary to Cooper et al. (2016), no cue was used in Study I of the present dissertation. However, the predictable task sequence in fixed-sequence blocks required participants to memorize the sequence to prepare for the upcoming task and this involved advance rule updating and working memory in Study I. This preparation can be proactive distractor suppression, but can also be general preparation for performing the upcoming task. This issue will be discussed later in section 3.2.

The results of the first two study showed that the engagement of proactive preparation doesn’t depend only on task predictability, but also on the participants incentivization. While the task sequence in Study I was predictable only in half of blocks (fixed vs. random blocks), it could always be predictable in Study II, but with different prediction reliability (high-predictable vs. low-predictable). Due to the experimental design, in half of blocks in Study I (random-sequence blocks) no proactive preparation could get engaged. In contrast, providing participants with some degrees of predictability in Study II could motivate participants to engage in proactive preparation. Moreover, In Study I, task predictability changed randomly across blocks from fixed- to random-sequence and vice versa. Thus, there was no guarantee for retaining the current preparation strategy when shifting to the next block. From this perspective, preparation before stimulus onset could be optimally beneficial only if there was an urgent need for proactive task-set reconfiguration because of the harder task switching (i.e., task switching in the color group) and it could be postponed to the period after stimulus onset if task switching is easier (i.e., task switching in the shape group). Consistent with this, in Study I, participants in the shape group didn’t appear to prepare much before stimulus onset, but did it soon after stimulus as reflected in an increased early Pd in predictable than in unpredictable sequence blocks. This is well in line with the expectation, as the early Pd reflects proactive suppression of the distractor which occurs shortly after stimulus onset (van Zoest et al., 2021; van Moorselaar et al., 2021; Weaver et al., 2017).

In Study II, predictability remained the same during the entire session. Therefore, an adapted strategy could be used for a long time, incentivizing all participants to prepare proactively. However, as in Study I, participants in the color group again had more motivation to prepare proactively due to harder task switching. Consistent with this, they exerted a stronger early suppression in high-predictable trial sequences to proactively suppress the color distractor than in low-predictable trial sequences. These findings are consistent with other studies which showed a propensity toward proactive preparation when the task is difficult (Conci, Dieschsel, Müller, & Töllner, 2019; Liu, Lin, Zhao, & Roberson, 2016) or when the distractor information is reliable (Heuer & Schubö, 2020; van Moorselaar, Lampers, Cordesius, & Slagter, 2020). Participants in the shape group were not incentivized to exert any early distractor suppression, maybe because knowledge about the dimension was already enough to perform optimally and knowing the exact feature of the target and distractor couldn’t enhance the performance.

In sum, the first two study showed an efficient attentional selection in the predictable task sequence which is implemented via proactive preparation. This proactive preparation could get engaged before stimulus onset, but it could also be postponed to early latencies after stimulus onset depending on the participant’s incentivization.

3.1.3 …social value

Social value is another factor which has been shown to influence task performance, especially when humans interact with others in joint action tasks (Saunders et al., 2019; Atmaca et al., 2011). In joint action literature, joint attention is an important factor and refers to directing attention to a common point in the space to achieve a successful task co-representation (Lachat et al., 2012; Michael et al., 2016). Study IV adapted a famous paradigm used in visual attention research – additional singleton paradigm (Theeuwes, 1992) – to investigate the neurophysiological correlates of joint attention in joint action. The task in Study IV consisted of eight equidistance Gabor stimuli on an imaginary circle from which two were colored and six were gray. Participants were sitting side-by-side and their task was to report the orientation of the Gabor patch in their assigned color while one participant's EEG (the agent) was recorded. When a participant's target was not presented, they were supposed to click on the "No target" button. Lateralized alpha-band power was used to evaluate spatial attentional selection (Bacigalupo & Luck, 2019; van Diepen et al., 2016; Klimesch, 2012; Thut et al., 2006; Worden et al., 2000).

The time-frequency results of Study IV revealed a negative laterization of the posterior alpha-band power elicited by the partner target and a positive lateralization of the posterior alpha-band power elicited by the non-relevant distractor. This finding suggests attentional capture by the partner target, but attentional suppression of the non-relevant distractor. This result is not trivial for two reasons: First, both the partner target and the non-relevant distractor were non-target for the agent. In this scenario the best strategy would be to suppress any non-target salient stimuli to efficiently direct the attention toward the target (Sawaki & Luck, 2010; Gaspelin & Luck, 2018; Luck et al., 2021). However, the EEG results showed that this is not the case and the social identity the stimuli influences attentional deployment of the agent when sharing a task. Second, the partner target and the non-relevant distractor were of equal luminance and similar saliency. Previous studies have shown differential processes of two singletons when one singleton (mainly the distractor) is more salient than the other (mainly the target) singleton (Theeuwes, 2010; Gaspelin & Luck, 2018). Despite the similar luminance between the partner target and non-relevant distractor and the fact that both these stimuli were a non-target for the agent, the partner target captured the agent's attention while the non-relevant distractor was suppressed. The finding suggests a pronounced role of social value in selective attention.

Behavioral and electrophysiological results of Study IV can also be interpreted within the framework of the most well-known theories in joint action such as action co-representation account (Sebanz et al., 2003, 2006) and referential coding account (Dolk et al., 2013; 2014). According to action co-representation account, the joint Simon effect is a consequence of the interference between the agent's representation of their own action and the agent's representation of the partner's action; reflected in longer RTs in incompatible compared to in compatible trials (Sebanz et al., 2003; Tsai et al., 2006; Freundlieb et al., 2017). Similarly, presentation of the partner target in Study IV activated the representation of the partner's action by the agent. This was extremely detrimental when the agents target was not present and they had to click on the "No target" button. In this case, presentation of the partner's action interferes with the agent's action to a stronger degree because the agent and the partner perform two different responses (the agent clicks on "No target" while the partner report the orientation) and this interference deteriorates the agent's performance. This might be the reason for observing the partner target slowing down the agent's performance to a stronger degree when the agent target was absent.

According to the referential coding account, participants code the stimulus feature which is instrumental in resolving the task. For instance, in a study by Sellaro et al. (2015) the response buttons were in red and green, and the participant's task was to respond to the shape dimension (triangle vs. circle) of the stimuli which could be either in red or green. In this case the referential coding account suggests that although the color is a task-irrelevant dimension, the agent would code the color of the stimuli because it is instrumental in response discrimination. As a consequence, RTs are longer when the agent target shares the color with the partner's response button (Sellaro et al., 2015). The results of Study IV showed that coding of the stimulus feature does not necessarily require a dimensional overlap between stimuli and the response button as long as a feature refers to the partner's action. More specifically, the presence of the partner in the experimental chamber enables the coding of the partner target's color as relevant, and thereby, deterioration of the agent performance when the partner target is present.

In sum, the results of Study IV suggest that, not only the saliency or goal-relevance of a stimulus, but also the social value of the stimulus determines when to attentionally select or suppress the stimulus.

3.1.4 …social context

A large proportion of the tasks that we share with other people can be categorized as cooperative or competitive tasks. Previous research has shown that performing cooperative joint action tasks with a positive relationship increases the impact of the partner target on the agent's action. On the other hand, engagement in competitive joint action tasks with negative relationship have been shown to reduce the impact of the partner target on the agent's performance (Hommel et al., 2009; Ruissen & de Bruijn, 2016; Mendl et al., 2018). Despite the ample behavioral evidence for such influences, neurophysiological mechanisms underlying the influence of the social context on joint task performance is missing.

The results of Study IV showed a negative lateralization of posterior alpha-band power elicited by the partner target in the cooperative condition, while the partner target in the competitive condition elicited a positive lateralization of posterior alpha-band power. One of the most well-known findings regarding cortical oscillations in the range of alpha-band is that decreased posterior alpha-band power is associated with attentional selection and increased posterior alpha-band power is associated with attentional suppression (Jensen & Mazaheri, 2010; Klimesch, 2012; Clayton et al., 2015; 2018; Bacigalupo & Luck, 2019; Foster & Awh, 2019). Considering this notion, the above-mentioned results suggest differential attentional processing of the partner target depending on the social context. The results of Study IV suggest that agents deploy attention to the partner target in the cooperative condition, but suppress the partner target in the competitive condition. One other alternative explanation for this differential process of partner target depending on the social context is the degree of action integration or segregation by the agent (Novembre, Sammler, & Keller, 2016). Competitive co-actors have been shown to segregate their actions to achieve better task performance (Hommel et al., 2009). The results of Study IV further suggest that the segregation of the agent's action from the partner's action representation required suppression of the partner target. This was reflected in a positive lateralization of alpha-band power in the competitive condition.

It is necessary to remind that the social context influenced only the lateralized alpha-band power elicited by the partner target and not by the non-relevant distractor. That is, the lateral non-relevant distractor elicited positive lateralization on alpha-band power in both cooperative and competitive conditions. However, for the partner target, the polarity of alpha-band lateralization highly depended on the social relationship and was positive in the competitive and was negative in the cooperative conditions. Furthermore, the physical characteristic of the partner target remained the same in cooperative and competitive conditions and no differential pattern of alpha-band lateralization can be attributed to the physical difference between stimuli. Based on these, it can be concluded that social context impacts the processing of the partner target and not the non-relevant distractor, although they are both non-targets for the agent. This finding suggests that participants tune their attention toward a stimulus depending on the social context, but only when the stimulus is relevant to the co-actor.

In sum, Study IV showed the influence of social context on attention selection of the partner target. The agents deploy attention to the partner target in the cooperative condition, but suppress it in the competitive condition.

3.2 Combined influence of task preparation and selection history on distractor suppression

As mentioned earlier, when participants switch between different tasks, they need to reconfigure their task sets such as recalling the rules of the new task, adjusting effectors, and adjusting target and distractor template (Monsell, 2003; Rogers & Monsell, 1995; Monsell & Mizon, 2006; Karayanidis et al., 2010). However, when the task is predictable, part of this reconfiguration can be accomplished before stimulus onset (Wolff et al., 2017; Rogers & Monsell, 1995), referred to as proactive control mechanism (Braver, 2012; Koch et al., 2018). Since more reconfiguration is needed in switch than in repetition trials, proactive preparation would be expected to be more prominent in switch than in repetition trials.

The time-frequency analysis in Study I quantified proactive preparation using posterior pre-stimulus alpha-band power. In line with the literature, the posterior pre-stimulus alpha-band power in the search task was reduced in switch than in repetition trials, only in fixed-sequence blocks (Wolff et al., 2017; Cooper et al., 2016; Gladwin & de Jong, 2005). Selection history, however, seemed to have a determinant influence on the strength of proactive preparation. More specifically, participants in the color group who had a harder time switching from the categorization to the search task showed a greater reduction of pre-stimulus alpha-band power than participants in the shape group. The color group participants had to select the color singletons in the categorization task, but suppress the color singleton and select the shape singleton in the search task. Participants in the shape group, however, just needed to select the shape singletons in both tasks. More effort and need for task-set reconfiguration, therefore, were expected in the color group than in the shape group. This reconfiguration could, at least partially, be accomplished proactively before stimulus onset and was reflected in pre-stimulus alpha-band power. Engagement of proactive preparation before stimulus onset was reflected in the behavior of the participants. As the marginal interaction in Study I and the significant interaction in Study II showed, the behavioral distractor cost in the more predictable task sequence (fixed-sequence trials in Study I and high-predictable trials in Study II) was smaller than that of the less predictable task sequence (random-sequence trials in Study I and low-predictable trials in Study II), but only for the participants in the color group. These findings suggest that stronger proactive preparation facilitates distractor handling.

One potential question is whether proactive preparation observed in the pre-stimulus alpha-band power in the search task of Study I reflects proactive distractor suppression or a general preparation (e.g., a combination of target enhancement, distractor suppression, and effector selection). If the reduced pre-stimulus alpha-band in switch trials reflects a general preparatory process, the same pattern would have been observed in the categorization task. However, for both groups there was no significant difference in posterior pre-stimulus alpha-band power between switch and repetition trials in the categorization task. This suggests that the observed pre-stimulus alpha-band modulation in the search task might reflect proactive distractor suppression (van Zoest et al., 2021; Wang et al., 2019; Serences, Yantis, Culberson, Awh, 2004). At first glance, these findings might be in contrast with the literature, which have shown no changes in the pre-stimulus alpha-band power when the location of the distractor was cued (Noonan et al., 2016) or when the distractor appeared in an expected location (van Moorselaar & Slagter, 2019; van Moorselaar et al., 2020). However, some recent studies have reported increased pre-stimulus alpha-band power when the distractor appears in a high probable location (Wang et al., 2019), or when the distractor's location or feature are cued (van Zoest et al., 2021). One conclusion from these contradictory results in different studies and Study I is that proactive distractor suppression via modulations of alpha-band power can be established proactively, only if participants are required or motivated to do so. The observation that proactive distractor suppression is reflected in alpha-band power might originate from the fact that participants in the color group had to exert this proactive preparation to a larger extent to compensate for the harder task switching process, a process which can be less effortful for the shape group participants who faced an easier task switching.

The structure of the search array could be another determinant factor in engagement of the proactive distractor suppression. For instance, when the target and distractor are in different quadrants of the visual field, suppression of the distractor might not affect the resolution of the target (Noonan et al. 2016). That is why participants might not even need to exert proactive distractor suppression. However, in the search task of Study I, the target and distractor were separated only with one gray distractor, meaning that they were in rather close proximity. This might be another reason for the engagement of the proactive distractor suppression via reduced posterior pre-stimulus alpha band power.

Therefore, the exerted proactive preparation before stimulus onset was shown to be influenced by individual selection history as well as task predictability. Moreover, the results of Studies I and II showed that the influence of selection history and prediction on proactive preparation is also reflected in early Pd amplitude, indicative of rapid, stimulus-driven distractor suppression (Weaver et al., 2017; van Zoest et al., 2021). In Study I, the early Pd was larger in predictable than in unpredictable sequence block, but only for participants in the shape group. Participants in the color group who had already performed a strong proactive task-set reconfiguration before stimulus onset, didn’t need to exert early distractor suppression anymore. However, participants in the shape group who showed weaker proactive task-set reconfiguration needed to exert a stronger early distractor suppression. One speculation would be that participants in the shape group didn’t opt to proactively suppress the distractor before stimulus onset because it would have been effortful and costly. The engagement of pre-stimulus distractor suppression before all search trials would have been ineffective in those search trials without a color distractor. However, this was not the case for the color group as they always needed to suppress the color dimension when switching to the search task. Therefore, the best strategy for participants in the shape group would be to exert an early distractor suppression after stimulus onset, only when the color distractor was present (Noonan et al., 2016).

In Study II, however, the pattern of the early Pd in high-predictable trials sequence seemed to be reversed when compared to the early Pd in Study I. More specifically, participants in the color group showed a larger early Pd in high-predictable than in low-predictable trial sequence, while such effect was not seen in the shape group. There are two reasons for such a difference between the results of Study I and II. First, in half of the blocks in Study I, the task sequence was completely unpredictable while the task sequence in Study II was always predictable albeit with different levels of predictability. Second, predictable and unpredictable sequence blocks in Study I were mixed randomly within a session, while the task predictability in Study II was constant within a session. Because of these, color group participants were more motivated to exert an early distractor suppression in the predictable task sequence in Study II than in Study I and as it was reflected in an enhanced early Pd amplitude for the color group in high-predictable task sequences in Study II. The predictability seemed to have no influence on early distractor suppression in the shape group in Study II, maybe because these participants didn’t need a 100% predictable task sequence for optimal distractor handling. Participants in the shape group had to respond to the shape singleton and ignore the color distractor in all tasks and precise featural information about the distractor seemed of no benefit in early distractor suppression (Liesefeld & Müller, 2019).

Therefore, task predictability impacts proactive distractor suppression, depending on the individual selection history. Reactive distractor suppression was the next step of distractor suppression which comes to the play after proactive distractor suppression. As the ERP results of Study II showed, the late Pd was larger in the color group than in the shape group, suggesting more need for reactive distractor suppression by the color group participants. However, the higher predictability reduced the amplitude of the late Pd equally for both groups. The reduced amplitude of the late Pd has already been linked to the less need for reactive distractor suppression and easier distractor handling (Heuer & Schubö, 2020; van Moorselaar & Slagter, 2019; Henare et al., 2020) because the color distractor might not trigger a strongly surprising attend-to-me signal (Gaspelin & Luck, 2018). For instance, the recent research by van Moorselaar and Slagter (2019) showed absence of the late Pd when the distractor repeatedly appeared in a location. The authors suggested that when the location of the distractor is predictable, there is no need for reactive suppression of the distractor, because it is learnt to ignore the distractor safely without deploying attention to that or without actively suppressing it. Although selection history in Study II didn’t have any impact on the utilization of task predictability in enhancing reactive distractor suppression, the color group participants always needed stronger reactive distractor suppression in the search task due to their individual selection history.

In sum, increasing task predictability was shown to enhance proactive distractor suppression which can be engaged either before stimulus onset (pre-stimulus alpha band power) or very early after stimulus onset (the early Pd). Engagement of proactive distractor suppression was shown to be a function of individual selection history. Reactive distractor suppression, however, was enhanced when task predictability increased, irrespective of individual selection history.

3.3 Combined influence of task preparation and selection history on attentional selection

It has been well-investigated that increased task predictability enhances resolution of the target selection (Posner, 1980, Burra & Kerzel, 2013). Target selection is faster when the exact features of the target are known (Burra & Kerzel, 2013), when the target location is cued (Wildegger et al., 2017; Noonan et al., 2016), when the target identity is cued (Wildegger et al., 2017), or when the target appears in a high probable location (Ferrante et al., 2018; Geng & Behrmann, 2005). Providing participants with such foreknowledge about the target has been shown to enhance the size of the target N2pc, which is a marker of the covert deployment of visual attention to the target (Noonan et al., 2016; Burra & Kerzel, 2013).

Besides task predictability, selection history is another factor which strongly impacts the target N2pc. For instance, Feldmann-Wüstefeld et al. (2015) manipulated individual selection history of participants similar to what was done in Studies I and II. Subsequently, both groups performed a search task in which all participants reported the orientation of the line inside a shape target while a color singleton was present in some trials. Their search task results showed a later N2pc onset latency in the color group than in the shape group when the singletons appeared in opposite hemifields. Later, Kadel et al. (2017) showed that this effect of selection history on target selection persist when the task sequence is fully predictable or even when the search task is performed on a separate day, and disappears after the completion of several hundreds of search trials.

Therefore, both task predictability and selection history seem to have prominent influence on target selection. One aim of Studies I and II was to examine the combined influence of selection history and task predictability on target selection. In both studies, participants in the color group seemed to benefit more from task predictability when the color distractor was absent. While a marginal interaction in study I showed larger target N2pc in fixed- than in random-sequence block only for participants in the color group, this finding was confirmed by the significant interaction in Study II. However, when target and distractor were in opposite hemifields, the task predictability seemed to lose power in modulating the N2pc characteristics in the color group. More specifically, and in line with previous studies (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017), when the singletons were in opposite hemifields, the N2pc was delayed in the color group than in the shape group. Importantly, the N2pc onset was similar between fixed-sequence blocks and random-sequence blocks. This finding suggests that, although participants exert proactive preparation when is possible, this preparation can’t fully negate selection history attentional biases when selecting the target.

One reason for the later N2pc onset in the color than in the shape group may be due to the fact that the color distractor has a higher salience for the color group participants due to their selection history and therefore competes stronger in capturing attention (Wykowska & Schubö, 2011). Although the results of Study I showed no electrophysiological evidence for attentional capture (no distractor N2pc; Feldmann-Wüstefeld et al., 2015), the color distractor was salient enough to delay attentional deployment to the target for the color group participants. However, the fact that the color singleton couldn’t capture attention was challenged by Study II. In this study, the lateral color distractor in the search task elicited a N2pc in low-predictable sequence trials in the color group indicating attentional capture by the color distractor (Sawaki & Luck, 2010; Liesefeld et al., 2017; Berggren & Eimer, 2018). Notably, the distractor N2pc in the color group disappeared when the task sequence was fully predictable, highlighting the potency of proactive preparation in reducing selection history biases. Emergence of the distractor N2pc in low-predictable conditions is in line with the rapid-disengagement theory (Theeuwes, 2010). As this theory posits, a salient distractor captures attention as reflected in the N2pc. However, attention is disengaged shortly after capture as soon as top-down suppression is engaged and suppresses the singleton which is distinguished to be a distractor. Although distractor N2pc is not reflected in the ERP in high-predictable sequence trials, when looking at the behavioral results, the distractor cost in the color group in high-predictable sequence trials was still twice as large compared to the shape group. Again, this confirms the impotency of proactive preparation in overriding the selection history attentional biases.

In sum, previous experience with a feature dimension was shown to reduce resolution of the target selection when distractor shared the dimension with individual selection history. Although increasing task predictability enhanced the target selection, it couldn’t negate residual selection history biases.

3.4 Disentangling the functional significance of the early Pd and Ppc

One of the controversial debates within the last decade has been to distinguish between two lateralized ERP components, namely the Ppc and the early Pd. Both components emerge as contralateral positivity to the location of the salient stimulus at ~100 ms after stimulus onset in parieto-occipital sites. Despite these similarities, the early Pd and the Ppc components have a prominent difference which is in their functional significance. The Ppc component has been shown to be sensitive only to the physical salience of the stimuli and not to the context (Corriveau et al., 2012; Jannati et al., 2013; Pomerleau et al., 2014). For instance, the amplitude and latency of the Ppc are similar irrespective of whether it is triggered by the target or the distractor (Pomerleau et al., 2014). Based on this finding, Pomerleau and colleagues suggest that the Ppc is a reflector of brain responses to the imbalance of visual sensory input and it is irrelevant to the attentional load, task context, or stimulus status (target or distractor). The early Pd, on the other hand, has been shown to be flexible depending on contextual manipulations such as increasing expectation about the distractor location (van Moorselaar et al., 2021) or cuing the distractor location or feature (van Zoest et al., 2021). For instance, when the exact feature of the distractor in the upcoming trial is cued and participants can proactively suppress the upcoming distractor, less rapid stimulus-driven suppression is needed and is reflected in a reduced amplitude of the early Pd (van Zoest et al., 2021).

The results of Studies I and II make a significant contribution to better understanding the functional significance of the early Pd and Ppc. For the Ppc, this component was mainly observed in the ERP results of the categorization tasks in Studies I and II. In the ERP results of the categorization task in Study I, when singletons were on the same side, both groups showed an early positivity. When singletons were on opposite sides, however, the color group still showed an early positivity in the ERP locked to the location of the color singleton, while the shape group showed an early negativity in the ERP locked to the location of the shape singleton. This early negativity shown by the shape group participants is, in fact, the Ppc emerging by the color singleton which is placed on the opposite side of the shape singleton. The early positivity observed in the categorization task is likely the Ppc because it follows the location of the color singleton, and its amplitude doesn’t change when task sequence varies between random- and fix-sequence blocks. This was further confirmed by the ERP results of the categorization task in Study II: When the color singleton was laterally presented, participants in both groups showed a strong Ppc which its amplitude was unchanged when the task predictability changed. Although the lateralized shape singleton seems to elicit the Ppc in both groups, however, the amplitude of the Ppc emerged by the shape singleton seems to be smaller than the Ppc amplitude elicited by the color singleton. This is not unexpected, because the color singleton has a higher salience than the shape singletons, and the brain needs to exert higher activation to process this imbalance in the sensory input, resulting in a larger Ppc (Pomerleau et al., 2014).

The early positivity in the search task in Studies I and II has a different pattern than that of the categorization task. In Study I the ERP results in the search task show an early positivity which its polarity tracks the location of the color singleton. It means, when the singletons are on the same side, the early positivity has a positive polarity, but when the color distractor appears on the opposite side, the early positive takes a negative polarity. Importantly, the amplitude of this early positivity was sensitive to contextual manipulations. More specifically, when the physical stimulation was unchanged, task sequence variation from random to fixed increased the amplitude of the early positivity, but only in the shape group. As explained earlier, the reason could be that the shape group participants, instead of strong proactive distractor suppression before stimulus onset, performed a proactive distractor suppression shortly after the stimulus onset which was reflected as a larger early Pd in fixed- than in random-sequence blocks. In Study II, where the implementation of proactive distractor suppression was facilitated, due to the constant level of task predictability in a session, participants in the color group exerted an enhanced early distractor suppression when predictability was higher, reflected in a larger early Pd in high- than in low-predictable trial sequences. Therefore, the early positivity in the search task seems to be a combination of Ppc, as its polarity tracks the location of the distractor, and the early Pd, as its amplitude is sensitive to the task context.

In sum, the functional significances of the early Pd and Ppc were clarified in two studies. This is not trivial since, to the best of my knowledge, Studies I and II are one of the first which could distinguish between early Pd and Ppc within an experiment. While Ppc is only sensitive to the physical salience, the early Pd is sensitive to the task predictability and selection history.

3.5 Future perspectives

A large proportion of this dissertation focuses on proactive processes – mainly proactive distractor suppression in the presence of selection history. Although the results of the first two studies provide strong evidence supporting the idea of proactive distractor suppression, considering the contradictory literature (van Zoest et al., 2021; Wang et al., 2019, but see Noonan et al., 2016; van Moorselaar et al., 2019; 2021), proactive distractor suppression still needs more clarification. One suggestion for further research is to combine distractor cueing and associative learning used in Studies I and II. Such that when mixing the categorization and search task in a fixed-sequence order, a cue could be added before some of the search task trials to inform the participants about the presence of the color distractor. This way, any differential pre-stimulus oscillation between cued and non-cued search task trials indexes the degree of proactive distractor suppression which each group exerts.

Another potential stream of research relevant to this dissertation is to investigate the combined influence of different forms of selection history on attentional selection. Recently Le Pelley and colleagues (Le Pelley, Ung, Mine, Most, Watson, Pearson, & Theeuwes, 2022) have examined the combined influence of reward learning associated with the distractor and statistical regularities associated with the distractor (Le Pelley et al., 2022, see also Kim & Anderson, 2019). The results have suggested additive effects of reward learning and statistical regularities on attentional selection. That is, although the high-reward distractor captures more attention than the low-reward distractor, their presence in a high probable location has a similar benefit in their suppression. Associative learning can also be combined with other forms of selection history such as statistical regularities. One potential design is to use the categorization task presented in Studies I and II and to divide the participants into the color group and the shape group. Subsequently, the categorization task is mixed with a search task randomly. Critically, one can present the color distractor more often (e.g. 65% of distractor-present trials) in one location while the color distractor appears in other locations with a lower probability (each location 5% of distractor-present trials). A basic expectation would be to observe a generally larger distractor cost in the color group than in the shape group. Critically, if the effects of associative learning and statistical regularities are additive, the presence of the distractor in a high-probable location would facilitate distractor suppression to the same extent in both groups. However, if the effects of associative learning and statistical regularities interact, suppression of the distractor in the high-probable location would be easier for the color group participants than for the shape group participants.

3.6 Conclusions

The present dissertation examines the influence of different factors such as previous experience, task predictability, social value and social context on attentional control, and especially, on attentional capture. It demonstrates that previous experience biases attentional selection in a persistent way. Importantly, it demonstrates that attentional biases induced by selection history are mediated by the engagement of proactive preparation which is utilized before stimulus presentation. However, this preparatory mechanism doesn’t have the potency to negate attentional biases induced by selection history. The present dissertation also demonstrates that the social value has a prominent impact on the perception of the stimuli. When a stimulus is related to the partner, it is processed differently than a non-relevant distractor. Furthermore, social context was proven to have a determinant impact on the processing of the partner target. The partner target captures attention when participants cooperate and is suppressed when participants compete.

In sum, the present dissertation provides strong evidence that attentional control is a flexible mechanism. That is, the degree to deploy attention or suppress stimuli depends on different factors such as previous experiences, the knowledge about the upcoming task, social value and social context.

REFERENCES

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(25), 10367–10371. https://doi.org/10.1073/pnas.1104047108

Arita, J. T., Carlisle, N. B., & Woodman, G. F. (2012). Templates for rejection: Configuring attention to ignore task-irrelevant features. *Journal of Experimental Psychology. Human Perception and Performance, 38*(3), 580–584. https://doi.org/10.1037/a0027885

Arrington, C. M., & Logan, G. D. (2004). The cost of a voluntary task switch. *Psychological science, 15*(9), 610–615. https://doi.org/10.1111/j.0956-7976.2004.00728.x

Arrington, C. M., & Logan, G. D. (2005). Voluntary task switching: chasing the elusive homunculus. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 31*(4), 683–702. https://doi.org/10.1037/0278-7393.31.4.683

Atmaca, S., Sebanz, N., & Knoblich, G. (2011). The joint flanker effect: Sharing tasks with real and imagined co-actors. *Experimental Brain Research, 211*(3-4), 371-385. https://doi.org/10.1007/s00221-011-2709-9

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences, 16*(8), 437–443. https://doi.org/10.1016/j.tics.2012.06.010

Bacigalupo, F., & Luck, S. J. (2019). Lateralized suppression of alpha-band EEG activity as a mechanism of target processing. *The Journal of Neuroscience, 39*(5), 900–917. https://doi.org/10.1523/JNEUROSCI.0183-18.2018

Bacon, W. F., & Egeth, H. E. (1994). Overriding stimulus-driven attentional capture. *Perception & Psychophysics, 55*(5), 485–496. https://doi.org/10.3758/bf03205306

Baess, P., & Prinz, W. (2015). My partner is also on my mind: Social context modulates the N1 response. *Experimental Brain Research, 233*(1), 105–113. https://doi.org/10.1007/s00221-014-4092-9

Baldi, P., & Itti, L. (2010). Of bits and wows: A Bayesian theory of surprise with applications to attention. *Neural Networks*, *23*(5), 649–666. https://doi.org/10.1016/j.neunet.2009.12.007

Barras, C., & Kerzel, D. (2017). Salient-but-irrelevant stimuli cause attentional capture in difficult, but attentional suppression in easy visual search. *Psychophysiology*, *54*(12), 1826–1838. https://doi.org/10.1111/psyp.12962

Bengson, J. J., Liu, Y., Khodayari, N., & Mangun, G. R. (2020). Gating by inhibition during top-down control of willed attention. *Cognitive Neuroscience, 11*(1-2), 60–70. https://doi.org/10.1080/17588928.2019.1648405

Berggren, N., & Eimer, M. (2019). The roles of relevance and expectation for the control of attention in visual search. *Journal of Experimental Psychology: Human Perception and Performance, 45*(9), 1191–1205. https://doi.org/10.1037/xhp0000666

Borji, A., Sihite, D. N., & Itti, L. (2013). What/where to look next? Modeling top-down visual attention in complex interactive environments. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 44*(5), 523-538. https://doi.org/10.1109/TSMC.2013.2279715

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences, 16*(2), 106 -113. https://doi.org/10.1016/j.tics.2011.12.010

Bruce, N., & Tsotsos, J. (2005). Saliency based on information maximization. *Advances in neural information processing systems, 18*. 155–162.

Buccino, G., Binkofski, F., & Riggio, L. (2004). The mirror neuron system and action recognition. *Brain and Language, 89*(2), 370–376. https://doi.org/10.1016/S0093-934X(03)00356-0

Burra, N., & Kerzel, D. (2013). Attentional capture during visual search is attenuated by target predictability: evidence from the N2pc, Pd, and topographic segmentation. *Psychophysiology, 50*(5), 422–430. https://doi.org/10.1111/psyp.12019

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2015). The roles of cortical oscillations in sustained attention. *Trends in Cognitive Sciences, 19*(4), 188–195. https://doi.org/10.1016/j.tics.2015.02.004

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *The European Journal of Neuroscience, 48*(7), 2498–2508. https://doi.org/10.1111/ejn.13747

Colzato, L. S., de Bruijn, E. R., & Hommel, B. (2012). Up to "me" or up to "us"? The impact of self-construal priming on cognitive self-other integration. *Frontiers in Psychology, 3*, 341. https://doi.org/10.3389/fpsyg.2012.00341

Conci, M., Deichsel, C., Müller, H. J., & Töllner, T. (2019). Feature guidance by negative attentional templates depends on search difficulty. *Visual Cognition, 27*(3–4), 317–326. https://doi.org/10.1080/13506285.2019.1581316

Cooper, P. S., Darriba, Á., Karayanidis, F., & Barceló, F. (2016). Contextually sensitive power changes across multiple frequency bands underpin cognitive control. *NeuroImage, 132*, 499–511. https://doi.org/10.1016/j.neuroimage.2016.03.010

Corriveau, I., Fortier-Gauthier, U., Pomerleau, V. J., McDonald, J., Dell’acqua, R., & Jolicoeur, P. (2012). Electrophysiological evidence of multitasking impairment of attentional deployment reflects target-specific processing, not distractor inhibition. *International Journal of Psychophysiology, 86*(2), 152–-159. https://doi.org/10.1016/j.ijpsycho.2012.06.005

de Bruijn, E. R., Miedl, S. F., & Bekkering, H. (2008). Fast responders have blinders on: ERP correlates of response inhibition in competition. *Cortex, 44*(5), 580-586. https://doi.org/10.1016/j.cortex.2007.09.003

Di Caro, V., Theeuwes, J., & Della Libera, C. (2019). Suppression history of distractor location biases attentional and oculomotor control. *Visual Cognition, 27*(2), 142-157. https://doi.org/10.1080/13506285.2019.1617376

Dittrich, K., Dolk, T., Rothe-Wulf, A., Klauer, K. C., & Prinz, W. (2013). Keys and seats: Spatial response coding underlying the joint spatial compatibility effect. *Attention, Perception & Psychophysics, 75*(8), 1725–1736. https://doi.org/10.3758/s13414-013-0524-z

Dittrich, K., Rothe, A., & Klauer, K. C. (2012). Increased spatial salience in the social Simon task: A response-coding account of spatial compatibility effects. *Attention, Perception & Psychophysics, 74*(5), 911–929. https://doi.org/10.3758/s13414-012-0304-1

Doesburg, S. M., Bedo, N., & Ward, L. M. (2016). Top-down alpha oscillatory network interactions during visuospatial attention orienting. *NeuroImage, 132*, 512–519. https://doi.org/10.1016/j.neuroimage.2016.02.076

Dolk, T., Hommel, B., Colzato, L. S., Schütz-Bosbach, S., Prinz, W., & Liepelt, R. (2014). The joint Simon effect: A review and theoretical integration. *Frontiers in Psychology, 5*, 974. https://doi.org/10.3389/fpsyg.2014.00974

Dolk, T., Hommel, B., Prinz, W., & Liepelt, R. (2013). The (not so) social Simon effect: A referential coding account. *Journal of Experimental Psychology. Human Perception and Performance, 39*(5), 1248–1260. https://doi.org/10.1037/a0031031

Eimer M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology, 99*(3), 225–234. https://doi.org/10.1016/0013-4694(96)95711-9

Eimer M. (2014). The neural basis of attentional control in visual search. *Trends in Cognitive Sciences, 18*(10), 526–535. https://doi.org/10.1016/j.tics.2014.05.005

Eimer, M., & Kiss, M. (2008). Involuntary attentional capture is determined by task set: evidence from event-related brain potentials. *Journal of Cognitive Neuroscience, 20*(8), 1423–1433. https://doi.org/10.1162/jocn.2008.20099

Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review, 25*(2), 514–538. https://doi.org/10.3758/s13423-017-1380-y

Failing, M., Wang, B., & Theeuwes, J. (2019). Spatial suppression due to statistical regularities is driven by distractor suppression not by target activation. *Attention, Perception & Psychophysics, 81*(5), 1405–1414. https://doi.org/10.3758/s13414-019-01704-9

Fecteau J. H. (2007). Priming of pop-out depends upon the current goals of observers. *Journal of Vision, 7*(6), 1. https://doi.org/10.1167/7.6.1

Feldman, H., & Friston, K. (2010). Attention, uncertainty, and free-energy. *Frontiers in Human Neuroscience, 4*, 215. https://doi.org/10.3389/fnhum.2010.00215

Feldmann-Wüstefeld, T., & Schubö, A. (2016). Intertrial priming due to distractor repetition is eliminated in homogeneous contexts. *Attention, Perception & Psychophysics, 78*(7), 1935–1947. https://doi.org/10.3758/s13414-016-1115-6

Feldmann-Wüstefeld, T., Uengoer, M., & Schubö, A. (2015). You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention. *Psychophysiology, 52*(11), 1483–1497. https://doi.org/10.1111/psyp.12514

Ferrante, O., Patacca, A., Di Caro, V., Della Libera, C., Santandrea, E., & Chelazzi, L. (2018). Altering spatial priority maps via statistical learning of target selection and distractor filtering. *Cortex, 102*, 67–95. https://doi.org/10.1016/j.cortex.2017.09.027

Folk, C. L., & Remington, R. (1998). Selectivity in distraction by irrelevant featural singletons: evidence for two forms of attentional capture. *Journal of Experimental Psychology. Human Perception and Performance, 24*(3), 847–858. https://doi.org/10.1037//0096-1523.24.3.847

Folk, C. L., & Remington, R. (2006). Top-down modulation of preattentive processing: Testing the recovery account of contingent capture. *Visual Cognition, 14*(4-8), 445-465. https://doi.org/10.1080/13506280500193545

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology. Human Perception and Performance, 18*(4), 1030–1044. https://doi.org/10.1037/0096-1523.18.4.1030

Fortier-Gauthier, U., Moffat, N., Dell'Acqua, R., McDonald, J. J., & Jolicœur, P. (2012). Contralateral cortical organisation of information in visual short-term memory: Evidence from lateralized brain activity during retrieval. *Neuropsychologia, 50*(8), 1748–1758. https://doi.org/10.1016/j.neuropsychologia.2012.03.032

Foster, J. J., & Awh, E. (2019). The role of alpha oscillations in spatial attention: Limited evidence for a suppression account. *Current Opinion in Psychology, 29*, 34–40. https://doi.org/10.1016/j.copsyc.2018.11.001

Foxe, J. J., Murphy, J. W., & De Sanctis, P. (2014). Throwing out the rules: Anticipatory alpha-band oscillatory attention mechanisms during task-set reconfigurations. *European Journal of Neuroscience, 39*(11), 1960–1972. https://doi.org/10.1111/ejn.12577

Franconeri, S. L., & Simons, D. J. (2003). Moving and looming stimuli capture attention. *Perception & Psychophysics, 65*(7), 999–1010. https://doi.org/10.3758/bf03194829

Freundlieb, M., Sebanz, N., & Kovács, Á. M. (2017). Out of your sight, out of my mind: Knowledge about another person's visual access modulates spontaneous visuospatial perspective-taking. *Journal of Experimental Psychology. Human Perception and Performance, 43*(6), 1065–1072. https://doi.org/10.1037/xhp0000379

Friston, K. (2009). The free-energy principle: A rough guide to the brain? *Trends in Cognitive Sciences, 13*(7), 293–301. https://doi.org/10.1016/j.tics.2009.04.005

Gaspelin, N., & Luck, S. J. (2018). The role of inhibition in avoiding distraction by salient stimuli. *Trends in Cognitive Sciences, 22*(1), 79–92. https://doi.org/10.1016/j.tics.2017.11.001

Gaspelin, N., Leonard, C. J., & Luck, S. J. (2015). Direct evidence for active suppression of salient-but-irrelevant sensory inputs. *Psychological Science, 26*(11), 1740–1750. https://doi.org/10.1177/0956797615597913

Geng, J. J., & Behrmann, M. (2005). Spatial probability as an attentional cue in visual search. *Perception & Psychophysics, 67*(7), 1252–1268. https://doi.org/10.3758/bf03193557

Gladwin, T. E., & de Jong, R. (2005). Bursts of occipital theta and alpha amplitude preceding alternation and repetition trials in a task--switching experiment. *Biological Psychology, 68*(3), 309–-329. https://doi.org/10.1016/j.biopsycho.2004.06.004

Händel, B. F., Haarmeier, T., & Jensen, O. (2011). Alpha oscillations correlate with the successful inhibition of unattended stimuli. *Journal of Cognitive Neuroscience, 23*(9), 2494–2502. https://doi.org/10.1162/jocn.2010.21557

Hanslmayr, S., Gross, J., Klimesch, W., & Shapiro, K. L. (2011). The role of α oscillations in temporal attention. *Brain Research Reviews, 67*(1-2), 331–343. https://doi.org/10.1016/j.brainresrev.2011.04.002

Hauswald, A., Tucciarelli, R., & Lingnau, A. (2018). MEG adaptation reveals action representations in posterior occipitotemporal regions. *Cortex, 103*, 266–276. https://doi.org/10.1016/j.cortex.2018.03.016

Henare, D. T., Kadel, H., & Schubö, A. (2020). Voluntary Control of Task Selection Does Not Eliminate the Impact of Selection History on Attention. *Journal of Cognitive Neuroscience, 32*(11), 2159–2177. https://doi.org/10.1162/jocn_a_01609

Heuer, A., & Schubö, A. (2020). Cueing distraction: Electrophysiological evidence for anticipatory active suppression of distractor location. *Psychological Research, 84*(8), 2111–2121. https://doi.org/10.1007/s00426-019-01211-4

Heuer, H., Schmidtke, V., & Kleinsorge, T. (2001). Implicit learning of sequences of tasks. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 27*(4), 967–983. https://doi.org/10.1037/0278-7393.27.4.967

Hickey, C., Chelazzi, L., & Theeuwes, J. (2010). Reward changes salience in human vision via the anterior cingulate. *The Journal of Neuroscience, 30*(33), 11096–11103. https://doi.org/10.1523/JNEUROSCI.1026-10.2010

Hickey, C., Di Lollo, V., & McDonald, J. J. (2009). Electrophysiological indices of target and distractor processing in visual search. *Journal of Cognitive Neuroscience, 21*(4), 760–775. https://doi.org/10.1162/jocn.2009.21039

Hickey, C., McDonald, J. J., & Theeuwes, J. (2006). Electrophysiological evidence of the capture of visual attention. *Journal of Cognitive Neuroscience, 18*(4), 604–613. https://doi.org/10.1162/jocn.2006.18.4.604

Hommel, B., Colzato, L. S., & van den Wildenberg, W. P. (2009). How social are task representations? *Psychological Science, 20*(7), 794–798. https://doi.org/10.1111/j.1467-9280.2009.02367.x

Hughes, S. W., Lörincz, M., Cope, D. W., Blethyn, K. L., Kékesi, K. A., Parri, H. R., Juhász, G., & Crunelli, V. (2004). Synchronized oscillations at alpha and theta frequencies in the lateral geniculate nucleus. *Neuron, 42*(2), 253–268. https://doi.org/10.1016/s0896-6273(04)00191-6

Itti, L., & Borji, A. (2015). Computational models: Bottom-up and top-down aspects. arXiv preprint arXiv:1510.07748.

Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews Neuroscience, 2*(3), 194–203. https://doi.org/10.1038/35058500

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 20*(11), 1254-1259. https://doi.org/10.1109/34.730558

Jannati, A., Gaspar, J. M., & McDonald, J. J. (2013). Tracking target and distractor processing in fixed-feature visual search: Evidence from human electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance, 39*(6), 1713–1730. https://doi.org/10.1037/a0032251

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience, 4*, 186. https://doi.org/10.3389/fnhum.2010.00186

Kadel, H., Feldmann-Wüstefeld, T., & Schubö, A. (2017). Selection history alters attentional filter settings persistently and beyond top-down control. *Psychophysiology, 54*(5), 736–754. https://doi.org/10.1111/psyp.12830

Karayanidis, F., Jamadar, S., Ruge, H., Phillips, N., Heathcote, A., & Forstmann, B. U. (2010). Advance preparation in task-switching: Converging evidence from behavioral, brain activation, and model-based approaches. *Frontiers in Psychology*, *1*, 25. https://doi.org/10.3389/fpsyg.2010.00025

Kelly, S. P., Lalor, E. C., Reilly, R. B., & Foxe, J. J. (2006). Increases in alpha oscillatory power reflect an active retinotopic mechanism for distracter suppression during sustained visuospatial attention. *Journal of Neurophysiology*, *95*(6), 3844–3851. https://doi.org/10.1152/jn.01234.2005

Kim, H., & Anderson, B. A. (2019). Dissociable components of experience-driven attention. *Current Biology, 29*(5), 841–845. https://doi.org/10.1016/j.cub.2019.01.030

Kiss, M., Grubert, A., Petersen, A., & Eimer, M. (2012). Attentional capture by salient distractors during visual search is determined by temporal task demands. *Journal of Cognitive Neuroscience, 24*(3), 749–759. https://doi.org/10.1162/jocn_a_00127

Klimesch W. (2012). α-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences, 16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Koch I. (2003). The role of external cues for endogenous advance reconfiguration in task switching. *Psychonomic Bulletin & Review, 10*(2), 488–492. https://doi.org/10.3758/bf03196511

Koch, I., Poljac, E., Müller, H., & Kiesel, A. (2018). Cognitive structure, flexibility, and plasticity in human multitasking-An integrative review of dual-task and task-switching research. *Psychological bulletin, 144*(6), 557–583. https://doi.org/10.1037/bul0000144

Lachat, F., Hugueville, L., Lemaréchal, J. D., Conty, L., & George, N. (2012). Oscillatory Brain Correlates of Live Joint Attention: A Dual-EEG Study. *Frontiers in Human Neuroscience*, *6*, 156. https://doi.org/10.3389/fnhum.2012.00156

Le Pelley, M. E., Beesley, T., & Griffiths, O. (2011). Overt attention and predictiveness in human contingency learning. *Journal of Experimental Psychology. Animal Behavior Processes, 37*(2), 220–229. https://doi.org/10.1037/a0021384

Le Pelley, M. E., Ung, R., Mine, C., Most, S. B., Watson, P., Pearson, D., & Theeuwes, J. (2022). Reward learning and statistical learning independently influence attentional priority of salient distractors in visual search. *Attention, Perception & Psychophysics*, *84*(5), 1446–1459. https://doi.org/10.3758/s13414-021-02426-7

Lien, M. C., Pedersen, L., & Proctor, R. W. (2016). Stimulus-response correspondence in go-nogo and choice tasks: Are reactions altered by the presence of an irrelevant salient object? *Psychological Research, 80*(6), 912–934. https://doi.org/10.1007/s00426-015-0699-0

Liesefeld, H. R., & Müller, H. J. (2019). Distractor handling via dimension weighting. *Current Opinion in Psychology, 29*, 160–167. https://doi.org/10.1016/j.copsyc.2019.03.003

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage, 156*, 166–173. https://doi.org/10.1016/j.neuroimage.2017.05.016

Liu, Q., Lin, S., Zhao, G., & Roberson, D. (2016). The effect of modulating top-down attention deployment on the N2pc/PCN. *Biological Psychology, 117*, 187–-193. https://doi.org/10.1016/j. biops ycho.2016.04.004

Liu, Z., de Zwart, J. A., Yao, B., van Gelderen, P., Kuo, L. W., & Duyn, J. H. (2012). Finding thalamic BOLD correlates to posterior alpha EEG. *NeuroImage, 63*(3), 1060–1069. https://doi.org/10.1016/j.neuroimage.2012.08.025

Luck, S. J., & Hillyard, S. A. (1994a). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology, 31*(3), 291–308. https://doi.org/10.1111/j.1469-8986.1994.tb02218.x

Luck, S. J., & Hillyard, S. A. (1994b). Spatial filtering during visual search: evidence from human electrophysiology. *Journal of Experimental Psychology. Human Perception and Performance, 20*(5), 1000–1014. https://doi.org/10.1037//0096-1523.20.5.1000

Luck, S. J., Gaspelin, N., Folk, C. L., Remington, R. W., & Theeuwes, J. (2021). Progress toward resolving the attentional capture debate. *Visual Cognition, 29*(1), 1-21. https://doi.org/10.1080/13506285.2020.1848949

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. Role of features. *Memory & Cognition, 22*(6), 657–672. https://doi.org/10.3758/bf03209251

Mayr, U., & Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. *Journal of Experimental Psychology: General, 129*, 4 –26. http://dx.doi.org/10.1037/0096-3445.129.1.4

Mazza, V., Turatto, M., & Caramazza, A. (2009). Attention selection, distractor suppression and N2pc. *Cortex, 45*(7), 879–890. https://doi.org/10.1016/j.cortex.2008.10.009

Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 22(6), 1423–1442. https://doi.org/10.1037/0278-7393.22.6.1423

Mendl, J., Fröber, K., & Dolk, T. (2018). Are you keeping an eye on me? The influence of competition and cooperation on joint Simon task performance. *Frontiers in Psychology, 9*, 1361. https://doi.org/10.3389/fpsyg.2018.01361

Michael, J., Sebanz, N., & Knoblich, G. (2016). Observing joint action: Coordination creates commitment. *Cognition, 157*, 106-113. https://doi.org/10.1016/j.cognition.2016.08.024

Monsell S. (2003). Task switching. *Trends in Cognitive Sciences, 7*(3), 134–140. https://doi.org/10.1016/s1364-6613(03)00028-7

Monsell, S., & Mizon, G. A. (2006). Can the task-cuing paradigm measure an endogenous task-set reconfiguration process? *Journal of Experimental Psychology: Human Perception and Performance, 32*, 493–516. http://dx.doi.org/10.1037/0096-1523.32.3.493

Monsell, S., Sumner, P., & Waters, H. (2003). Task-set reconfiguration with predictable and unpredictable task switches. *Memory & Cognition, 31*(3), 327–342. https://doi.org/10.3758/BF03194391

Müller, B., Brass, M., Kühn, S., Tsai, C. C., Nieuwboer, W., Dijksterhuis, A., & van Baaren, R. B. (2011). When Pinocchio acts like a human, a wooden hand becomes embodied. Action co-representation for non-biological agents. *Neuropsychologia, 49*(5), 1373–1377. https://doi.org/10.1016/j.neuropsychologia.2011.01.022

Naeem, M., Prasad, G., Watson, D. R., & Kelso, J. A. (2012). Electrophysiological signatures of intentional social coordination in the 10-12 Hz range. *NeuroImage, 59*(2), 1795–1803. https://doi.org/10.1016/j.neuroimage.2011.08.010

Noonan, M. P., Adamian, N., Pike, A., Printzlau, F., Crittenden, B. M., & Stokes, M. G. (2016). Distinct mechanisms for distractor suppression and target facilitation. *The Journal of Neuroscience, 36*(6), 1797–1807. https://doi.org/10.1523/JNEUROSCI.2133-15.2016

Novembre, G., Sammler, D., & Keller, P. E. (2016). Neural alpha oscillations index the balance between self-other integration and segregation in real-time joint action. *Neuropsychologia, 89*, 414-425. https://doi.org/10.1016/j.neuropsychologia.2016.07.027

Payne, L., Guillory, S., & Sekuler, R. (2013). Attention-modulated alpha-band oscillations protect against intrusion of irrelevant information. *Journal of Cognitive Neuroscience, 25*(9), 1463–1476. https://doi.org/10.1162/jocn_a_00395

Pearce, J. M., & Hall, G. (1980). A model for Pavlovian learning: Variations in the effectiveness of conditioned but not of unconditioned stimuli. *Psychological Review, 87*(6), 532–552. https://doi.org/10.1037/0033-295X.87.6.532

Peters, R. J., & Itti, L. (2007). Beyond bottom-up: Incorporating task-dependent influences into a computational model of spatial attention. *In 2007 IEEE conference on computer vision and pattern recognition (pp. 1-8).* IEEE. https://doi.org/10.1109/CVPR.2007.383337

Poljac, E., & Yeung, N. (2014). Dissociable neural correlates of intention and action preparation in voluntary task switching. *Cerebral Cortex, 24*(2), 465–-478. https://doi.org/10.1093/cerco r/bhs326

Pomerleau, V. J., Fortier-Gauthier, U., Corriveau, I., McDonald, J. J., Dell'Acqua, R., & Jolicœur, P. (2014). The attentional blink freezes spatial attention allocation to targets, not distractors: Evidence from human electrophysiology. *Brain Research, 1559*, 33–-45. https://doi.org/10.1016/j.brain res.2014.02.029

Posner M. I. (1980). Orienting of attention. *The Quarterly Journal of Experimental Psychology, 32*(1), 3–25. https://doi.org/10.1080/00335558008248231

Proskovec, A. L., Wiesman, A. I., & Wilson, T. W. (2019). The strength of alpha and gamma oscillations predicts behavioral switch costs. *NeuroImage, 188*, 274–281. https://doi.org/10.1016/j.neuroimage.2018.12.016

Ramnani, N., & Miall, R. C. (2004). A system in the human brain for predicting the actions of others. *Nature neuroscience, 7*(1), 85–90. https://doi.org/10.1038/nn1168

Rizzolatti, G., & Craighero, L. (2004). The mirror-neuron system. *Annual Review of Neuroscience, 27*, 169–192. https://doi.org/10.1146/annurev.neuro.27.070203.144230

Rogers, R. D., & Monsell, S. (1995). Costs of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General, 124*(2), 207–231. https://doi.org/10.1037/0096-3445.124.2.207

Ruff, C. C., & Driver, J. (2006). Attentional preparation for a lateralized visual distractor: Behavioral and fMRI evidence. *Journal of Cognitive Neuroscience, 18*(4), 522–538. https://doi.org/10.1162/jocn.2006.18.4.522

Ruissen, M. I., & de Bruijn, E. R. (2016). Competitive game play attenuates self-other integration during joint task performance. *Frontiers in Psychology, 7*, 274. https://doi.org/10.3389/fpsyg.2016.00274

Ruys, K. I., & Aarts, H. (2010). When competition merges people's behavior: Interdependency activates shared action representations. *Journal of Experimental Social Psychology, 46*(6), 1130-1133. https://doi.org/10.1016/j.jesp.2010.05.016

Sadaghiani, S., Scheeringa, R., Lehongre, K., Morillon, B., Giraud, A. L., & Kleinschmidt, A. (2010). Intrinsic connectivity networks, alpha oscillations, and tonic alertness: A simultaneous electroencephalography/functional magnetic resonance imaging study. *The Journal of Neuroscience, 30*(30), 10243–10250. https://doi.org/10.1523/JNEUROSCI.1004-10.2010

Saunders, D. R., Melcher, D., & van Zoest, W. (2019). No evidence of task co-representation in a joint Stroop task. *Psychological Research*, *83*(5), 852–862. https://doi.org/10.1007/s00426-017-0909-z

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, perception & psychophysics*, *72*(6), 1455–1470. https://doi.org/10.3758/APP.72.6.1455

Sawaki, R., Geng, J. J., & Luck, S. J. (2012). A common neural mechanism for preventing and terminating the allocation of attention. *The Journal of Neuroscience*, *32*(31), 10725–10736. https://doi.org/10.1523/JNEUROSCI.1864-12.2012

Schneider, D., Herbst, S. K., Klatt, L. I., & Wöstmann, M. (2022). Target enhancement or distractor suppression? Functionally distinct alpha oscillations form the basis of attention. *The European journal of neuroscience*, *55*(11-12), 3256–3265. https://doi.org/10.1111/ejn.15309

Sebanz, N., Bekkering, H., & Knoblich, G. (2006a). Joint action: Bodies and minds moving together. *Trends in Cognitive Sciences*, *10*(2), 70-76. https://doi.org/10.1016/j.tics.2005.12.009

Sebanz, N., Knoblich, G., & Prinz, W. (2003). Representing others' actions: Just like one's own? *Cognition, 88*(3), B11-B21. https://doi.org/10.1016/S0010-0277(03)00043-X

Sebanz, N., Knoblich, G., Prinz, W., & Wascher, E. (2006b). Twin peaks: An ERP study of action planning and control in coacting individuals. *Journal of Cognitive Neuroscience, 18*(5), 859-870. https://doi.org/10.1162/jocn.2006.18.5.859

Sebanz, N., Rebbechi, D., Knoblich, G., Prinz, W., & Frith, C. D. (2007). Is it really my turn? An event-related fMRI study of task sharing. *Social Neuroscience, 2*(2), 81-95. https://doi.org/10.1080/17470910701237989

Sellaro, R., Dolk, T., Colzato, L. S., Liepelt, R., & Hommel, B. (2015). Referential coding does not rely on location features: Evidence for a nonspatial joint Simon effect. *Journal of Experimental Psychology. Human Perception and Performance, 41*(1), 186–195. https://doi.org/10.1037/a0038548

Serences, J. T., Yantis, S., Culberson, A., & Awh, E. (2004). Preparatory activity in visual cortex indexes distractor suppression during covert spatial orienting. *Journal of Neurophysiology, 92*(6), 3538–3545. https://doi.org/10.1152/jn.00435.2004

Simon J. R. (1969). Reactions toward the source of stimulation. *Journal of experimental psychology, 81*(1), 174–176. https://doi.org/10.1037/h0027448

Stenzel, A., Chinellato, E., Bou, M., Del Pobil, Á. P., Lappe, M., & Liepelt, R. (2012). When humanoid robots become human-like interaction partners: corepresentation of robotic actions. *Journal of Experimental Psychology. Human Perception and Performance, 38*(5), 1073–1077. https://doi.org/10.1037/a0029493

Stilwell, B. T., Egeth, H., & Gaspelin, N. (2022). Electrophysiological Evidence for the Suppression of Highly Salient Distractors. *Journal of Cognitive Neuroscience*, *34*(5), 787–805. https://doi.org/10.1162/jocn_a_01827

Summerfield, C., & de Lange, F. P. (2014). Expectation in perceptual decision making: neural and computational mechanisms. *Nature Reviews Neuroscience, 15*(11), 745–756. https://doi.org/10.1038/nrn3838

Summerfield, C., Trittschuh, E. H., Monti, J. M., Mesulam, M. M., & Egner, T. (2008). Neural repetition suppression reflects fulfilled perceptual expectations. *Nature Neuroscience, 11*(9), 1004–1006. https://doi.org/10.1038/nn.2163

Tanner, J., & Itti, L. (2019). A top-down saliency model with goal relevance. *Journal of Vision, 19*(1), 11. https://doi.org/10.1167/19.1.11

Theeuwes J. (1992). Perceptual selectivity for color and form. *Perception & Psychophysics, 51*(6), 599–606. https://doi.org/10.3758/bf03211656

Theeuwes J. (2010). Top-down and bottom-up control of visual selection. *Acta Psychologica, 135*(2), 77–99. https://doi.org/10.1016/j.actpsy.2010.02.006

Theeuwes J. (2019). Goal-driven, stimulus-driven, and history-driven selection. *Current Opinion in Psychology, 29*, 97–101. https://doi.org/10.1016/j.copsyc.2018.12.024

Thut, G., Nietzel, A., Brandt, S. A., & Pascual-Leone, A. (2006). α-band electroencephalographic activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience, 26*(37), 9494-9502. https://doi.org/10.1523/JNEUROSCI.0875-06.2006

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*(1), 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Tsai, C. C., Kuo, W. J., Jing, J. T., Hung, D. L., & Tzeng, O. J. L. (2006). A common coding framework in self–other interaction: Evidence from joint action task. *Experimental Brain Research, 175*(2), 353-362. https://doi.org/10.1007/s00221-006-0557-9

van Diepen, R. M., Miller, L. M., Mazaheri, A., & Geng, J. J. (2016). The Role of Alpha Activity in Spatial and Feature-Based Attention. *eNeuro, 3*(5), ENEURO.0204-16.2016. https://doi.org/10.1523/ENEURO.0204-16.2016

van Moorselaar, D., & Slagter, H. A. (2019). Learning what is irrelevant or relevant: Expectations facilitate distractor inhibition and target facilitation through distinct neural mechanisms. *The Journal of Neuroscience, 39*(35), 6953–6967. https://doi.org/10.1523/JNEUROSCI.0593-19.2019 van Moorselaar, D., Daneshtalab, N., & Slagter, H. A. (2021). Neural mechanisms underlying distractor inhibition on the basis of feature and/or spatial expectations. *Cortex, 137*, 232–250. https://doi.org/10.1016/j.cortex.2021.01.010

van Moorselaar, D., Lampers, E., Cordesius, E., & Slagter, H. A. (2020). Neural mechanisms underlying expectation-dependent inhibition of distracting information. *eLife, 9*, e61048. https://doi.org/10.7554/eLife.61048

van Zoest, W., Huber-Huber, C., Weaver, M. D., & Hickey, C. (2021). Strategic distractor suppression improves selective control in human vision. *The Journal of Neuroscience, 41*(33), 7120–7135. https://doi.org/10.1523/JNEUROSCI.0553-21.2021

Vandierendonck, A., Liefooghe, B., & Verbruggen, F. (2010). Task switching: Interplay of reconfiguration and interference control. *Psychological Bulletin, 136*(4), 601–626. https://doi.org/10.1037/a0019791

Vogel, E. K., & Luck, S. J. (2000). The visual N1 component as an index of a discrimination process. *Psychophysiology, 37*(2), 190–203. https://doi.org/10.1111/1469-8986.3720190

Wang, B., & Theeuwes, J. (2018a). Statistical regularities modulate attentional capture. *Journal of Experimental Psychology. Human Perception and Performance, 44*(1), 13–17. https://doi.org/10.1037/xhp0000472

Wang, B., & Theeuwes, J. (2018b). How to inhibit a distractor location? Statistical learning versus active, top-down suppression. *Attention, Perception & Psychophysics, 80*(4), 860–870. https://doi.org/10.3758/s13414-018-1493-z

Wang, B., van Driel, J., Ort, E., & Theeuwes, J. (2019). Anticipatory distractor suppression elicited by statistical regularities in visual search. *Journal of Cognitive Neuroscience, 31*(10), 1535–1548. https://doi.org/10.1162/jocn_a_01433

Weaver, M. D., van Zoest, W., & Hickey, C. (2017). A temporal dependency account of attentional inhibition in oculomotor control. *NeuroImage, 147*, 880–894. https://doi.org/10.1016/j.neuroimage.2016.11.004

Wildegger, T., van Ede, F., Woolrich, M., Gillebert, C. R., & Nobre, A. C. (2017). Preparatory α-band oscillations reflect spatial gating independently of predictions regarding target identity. *Journal of Neurophysiology, 117*(3), 1385–1394. https://doi.org/10.1152/jn.00856.2016

Wolfe, J. M., Butcher, S. J., Lee, C., & Hyle, M. (2003). Changing your mind: on the contributions of top-down and bottom-up guidance in visual search for feature singletons. *Journal of Experimental Psychology. Human Perception and Performance, 29*(2), 483–502. https://doi.org/10.1037/0096-1523.29.2.483

Wolff, N., Zink, N., Stock, A. K., & Beste, C. (2017). On the relevance of the alpha frequency oscillation's small-world network architecture for cognitive flexibility. *Scientific Reports, 7*(1), 13910. https://doi.org/10.1038/s41598-017-14490-x

Woodman, G. F., & Luck, S. J. (2003). Serial deployment of attention during visual search. *Journal of Experimental Psychology: Human Perception and Performance, 29*(1), 121–138. https://doi.org/10.1037//0096-1523.29.1.121

Worden, M. S., Foxe, J. J., Wang, N., & Simpson, G. V. (2000). Anticipatory biasing of visuospatial attention indexed by retinotopically specific alpha-band electroencephalography increases over occipital cortex. *The Journal of Neuroscience*, *20*(6), RC63. https://doi.org/10.1523/JNEUROSCI.20-06-j0002.2000

Wöstmann, M., Alavash, M., & Obleser, J. (2019). Alpha oscillations in the human brain implement distractor suppression independent of target selection. *The Journal of Neuroscience*, *39*(49), 9797–9805. https://doi.org/10.1523/JNEUROSCI.1954-19.2019

Wöstmann, M., Herrmann, B., Maess, B., & Obleser, J. (2016). Spatiotemporal dynamics of auditory attention synchronize with speech. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(14), 3873–3878. https://doi.org/10.1073/pnas.1523357113

Wykowska, A., & Schubö, A. (2011). Irrelevant singletons in visual search do not capture attention but can produce nonspatial filtering costs. *Journal of cognitive neuroscience*, *23*(3), 645–660. https://doi.org/10.1162/jocn.2009.21390

Yeung N. (2010). Bottom-up influences on voluntary task switching: The elusive homunculus escapes. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *36*(2), 348–362. https://doi.org/10.1037/a0017894

ORIGINAL MANUSCRIPTS

This section contains a copy of the manuscripts involved in the present dissertation. When it is available, copies of the published articles are used. Otherwise the latest version of the "submitted" manuscripts are used.

Study I

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology*, *59*(4), e13987. https://doi.org/10.1111/psyp.13987

Received: 9 April 2021 | Revised: 20 October 2021 | Accepted: 28 November 2021

DOI: 10.1111/psyp.13987

PSYCHOPHYSIOLOGY WILEY

ORIGINAL ARTICLE

Combined influences of strategy and selection history on attentional control

Hossein Abbasi[1] | **Hanna Kadel**[1] | **Clayton Hickey**[2] | **Anna Schubö**[1]

[1]Cognitive Neuroscience of Perception and Action, Philipps-University of Marburg, Marburg, Germany

[2]School of Psychology and Center for Human Brain Health, University of Birmingham, Birmingham, UK

Correspondence
Hossein Abbasi, Experimental and Biological Psychology, Philipps-University Marburg, Gutenbergstraße 18, 35037 Marburg, Germany.
Email: hossein.abbasi@uni-marburg.de

Funding information
Deutsche Forschungsgemeinschaft, Grant/Award Number: IRTG 1901, SFB/TRR 135, TP B3 and project number 222641018; H2020 European Research Council, Grant/Award Number: INSENSE 804360

Abstract

Visual attention is guided by top-down mechanisms and pre-stimulus task preparation, but also by selection history (i.e., the bias to prioritize previously attended items). Here we examine how these influences combine. Two groups of participants completed two intermingled tasks. One task involved categorization of a unique target; one group categorized the target based on color, and the other based on shape. The other task involved searching for a target defined by unique shape while ignoring a distractor defined by unique color. Our expectation was that the search task would be difficult for the color-categorization group because their categorization task required attentional resolution of color, but the search task required that they ignore color. In some experimental blocks, trials from the two tasks appeared predictably, giving the color-categorization group an opportunity to strategically prepare by switching between color-prioritizing and shape-prioritizing attentional templates. We looked to pre-stimulus oscillatory activity as a direct index of this preparation, and to reaction times and post-stimulus ERPs for markers of resultant change in attentional deployment. Results showed that preparation in the color-categorization group optimized attentional templates, such that these participants became less sensitive to the color distractor in the search task. But preparation was not sufficient to entirely negate the influence of selection history, and participants in the color-categorization group continued to show a propensity to attend to the color distractor. These results indicate that preparatory effort can be scaled to the anticipated attentional requirements, but attention is nevertheless considerably biased by selection history.

KEYWORDS

attention capture, early Pd, ERPs, N2pc, pre-stimulus alpha-band, selection history

---

Hossein Abbasi and Hanna Kadel shared first authorship.

Psychophysiology. 2022;59:e13987.
https://doi.org/10.1111/psyp.13987

1 | INTRODUCTION

Our daily life consists of many circumstances where we must switch between cognitive tasks and adapt our behavior to new situations. To accomplish this, visual selective attention can be tuned to current task settings so that task-relevant stimuli are prioritized and task-irrelevant stimuli are ignored (Maunsell & Treue, 2006; Olivers et al., 2011). This attentional set affects neural processing from early in the visual hierarchy (Battistoni et al., 2017; Moore & Zirnsak, 2017) and prioritizes relevant stimuli while preventing or overcoming selection of distractors (see e.g., Ansorge et al., 2011; Kiss et al., 2013; Sawaki & Luck, 2013; Wykowska & Schubö, 2011). It relies on mnemonic representations of target and distractor templates and facilitates both target processing and the suppression of stimuli known to be task-irrelevant (see e.g., Arita et al., 2012; Feldmann-Wüstefeld & Schubö, 2016; Reeder et al., 2017; Vatterott & Vecera, 2012).

Proactive attentional set can be indexed in its impact on task completion, but it can also be directly assessed in brain activity prior to stimulus onset. For example, the power and phase of pre-stimulus alpha-band EEG oscillations predict subsequent detection rate and discrimination performance (Busch et al., 2009; Chaumon & Busch, 2014; van Dijk et al., 2008; Hanslmayr et al., 2007). The preparatory establishment of attentional control seems to be reflected in a systematic decrease of posterior alpha power (Capotosto et al., 2016; Clayton et al., 2018; Mathewson et al., 2014), in line with the idea that alpha desynchronization reflects a release from inhibition (Klimesch, 2012) and thus induces a state of perceptual readiness (Hanslmayr et al., 2011; Mathewson et al., 2012; Sawaki et al., 2015). Although some studies have challenged the direct relation between post-stimulus alpha-band power and attentional selection (Antonov et al., 2020; Gundlach et al., 2020; Zhigalov & Jensen, 2020), a recent study has provided convincing results supporting the notion that pre-stimulus alpha-band power directly impacts post-stimulus attentional selection (van Zoest et al., 2021). According to their findings, van Zoest et al. (2021) suggested that increased power of pre-stimulus alpha-band reflects an advanced suppression mechanism which results in less attentional capture and less need for distractor suppression after stimulus onset.

Alpha oscillations are also associated with cognitive flexibility in task switching paradigms. In paradigms requiring shifts in attentional strategy, cues identifying a task shift elicit a reduction of frontal alpha power, and this has been linked to the need to adjust attentional control settings in switch trials (e.g., Foxe et al., 2014; Gladwin & de Jong, 2005; Poljac & Yeung, 2014; Proskovec et al., 2019). This "task-set reconfiguration" requires effort (Mayr & Keele, 2000; Monsell, 2003; Monsell & Mizon, 2006), but has a direct benefit: when participants are given sufficient time between cue and task onset, the cue reduces task-switching costs (Monsell & Mizon, 2006).

Human observers are therefore equipped with a dynamic top-down control system that directs attention according to current task goals. However, other influences on attention can interfere with this optimization. In particular, attentional selection is strongly shaped by prior experience (Awh et al., 2012; Failing & Theeuwes, 2018; Ferrante et al., 2018). Aside from effects of prior reward (e.g., Anderson et al., 2011; Feldmann-Wüstefeld et al., 2016; Hickey et al., 2010), attention is biased toward stimuli that have been predictive, even when this predictive power has explicitly ended (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Le Pelley et al., 2011; O'Brien & Raymond, 2012). In Feldmann-Wüstefeld et al. (2015), for example, selection history was manipulated by having two groups of participants complete different categorization tasks with the same stimuli. One group categorized the shape of stimuli, the other the color, and both subsequently completed the same visual search task. In the search task, participants showed a pronounced attentional bias toward a task-irrelevant distractor defined in the feature dimension that had been predictive in the categorization task. Subsequent research has shown that this sustains even when participants are explicitly told that the tasks are unrelated and when the tasks are completed on different days. The lingering bias disappears only after several hundred visual search trials have been completed (Kadel et al., 2017).

Selective attention is thus sensitive to proactive top-down control on one hand and selection history on the other. How are these mechanisms related? How do we reconcile situations in which selection history is in conflict with top-down control settings? Can top-down control compensate for effects of selection history?

The mere possibility for top-down control seems to do little in negating the effect of selection history. We have recently found that the opportunity for trial-wise top-down preparation (enabled by pretrial cueing) will not override selection history effects (Kadel et al., 2017, Exp. 1 and 2). However, little is known about the mechanisms underlying proactive top-down preparation in situations with a selection history bias. The purpose of the current study is therefore to directly index the preparation of attentional control settings and determine if this preparation, when present, can compensate for individual selection history. We tracked proactive control in pre-stimulus alpha power (Schneider et al., 2021; van Zoest et al., 2021) and we looked at the post-stimulus ERP in switch trials to identify the effect of this preparation and the effect of selection history on stimulus processing. In the ERP, the early distractor positivity (early Pd; Hickey et al., 2009; Sawaki & Luck, 2010; Weaver et al., 2017; van Zoest et al., 2021) was employed to track rapid, stimulus-triggered suppression of irrelevant stimuli. The subsequent N2pc (Eimer, 1996; Luck & Hillyard, 1994a, 1994b) was used to index changes in the attentional resolution of attended stimuli. Both components emerge as voltage differences across visual cortex ipsilateral and contralateral to eliciting stimuli.

We manipulated selection history by having participants complete two intermingled types of trial. In one trial type, they categorized stimuli that varied in color and shape (Figure 1a). Half of the participants (color-categorization group) were required to categorize the uniquely-colored stimulus (blue vs. green), while the other half (shape-categorization group) were required to categorize the uniquely-shaped stimulus (triangles vs. pentagons). In the other type of trial, all participants completed a visual search task that required them to attentionally select a uniquely shaped target and ignore a uniquely colored distractor (Figure 1b). For the color-categorization group, the predictive dimension in the categorization task was task-irrelevant and potentially distracting in the search task. For the shape-categorization group, in contrast, the predictive dimension in the categorization task was also relevant in the visual search task.

To provide the opportunity for proactive attentional control, the categorization and search tasks were performed within the same experiment, but the sequence of trial types changed between blocks (Figure 2a). In random-sequence blocks, the tasks were intermingled unpredictably so that no task-specific proactive preparation was possible. In fixed-sequence blocks, the tasks alternated in a fixed, predictable pattern. Our expectation was that participants would proactively reconfigure their attentional control settings in fixed-sequence blocks, where such preparation was possible, and that this would be reflected in preparatory oscillations in the alpha frequency band and in effects on behavior, Pd, and N2pc.

Most importantly, we were interested in whether proactive attentional control in fixed-sequence blocks would differ between the color- and shape-categorization groups. Participants in the shape-categorization group could rely on a similar attentional set for both the categorization and search tasks, because in both cases the target stimulus was defined in the same featural dimension. In contrast, participants in the color-categorization group attended to color targets in categorization trials, but shape targets in search trials, and therefore had to substantially reconfigure attentional control when the task switched. Our expectation was that correlates of reconfiguration would therefore emerge prominently when participants in the color-categorization group completed switch trials in fixed-sequence blocks. If participants are able to properly reconfigure in this circumstance, we expected this to benefit their attentional control in fixed-sequence blocks. As a result, in the search task, the color-categorization group should demonstrate less attentional capture in fixed-sequence blocks relative to random-sequence blocks.

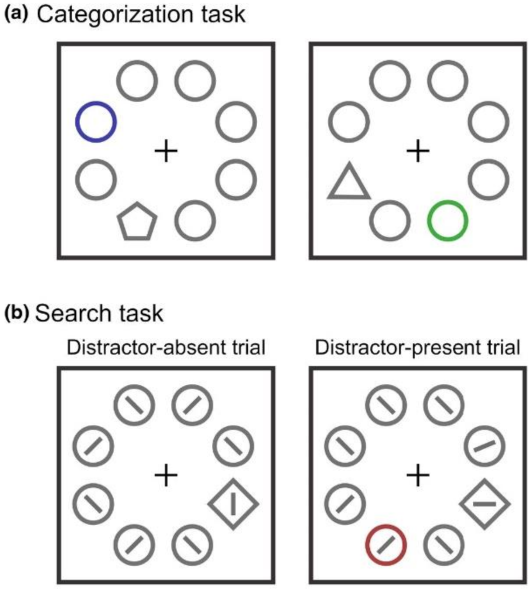


FIGURE 1 (a) Exemplary displays in the categorization task. Participants in the color-categorization group had to press one button for a green and another button for a blue circle. Participants in the shape-categorization group had to press one button for a pentagon and another button for a triangle. Participants were naïve to their group assignment when the experiment started and had to learn on a trial-and-error basis by receiving immediate auditory feedback in incorrect trials. (b) Exemplary displays in the search task. Both groups searched for the diamond-shaped target and reported the orientation (horizontal vs. vertical) of the embedded line. In 60% of the trials, an additional color distractor was presented (right panel) which had to be ignored

2 | METHOD

2.1 | Participants

Forty volunteers (9 male) participated in the experiment for course credit or monetary payment (8€/h). Written consent for participation was obtained before the experimental session. All but two participants were right-handed and all had normal or corrected-to-normal vision. Eight participants had to be excluded from analysis due to excessive eye movement artefacts in EEG data (over 25% of the trials; see below for details). Of the remaining 32 participants (6 male), 16 were assigned to the color-categorization group (mean age ± SD: 23.5 ± 2.5 years) and 16 to the shape-categorization group (mean age ± SD: 23.3 ± 2.5 years).

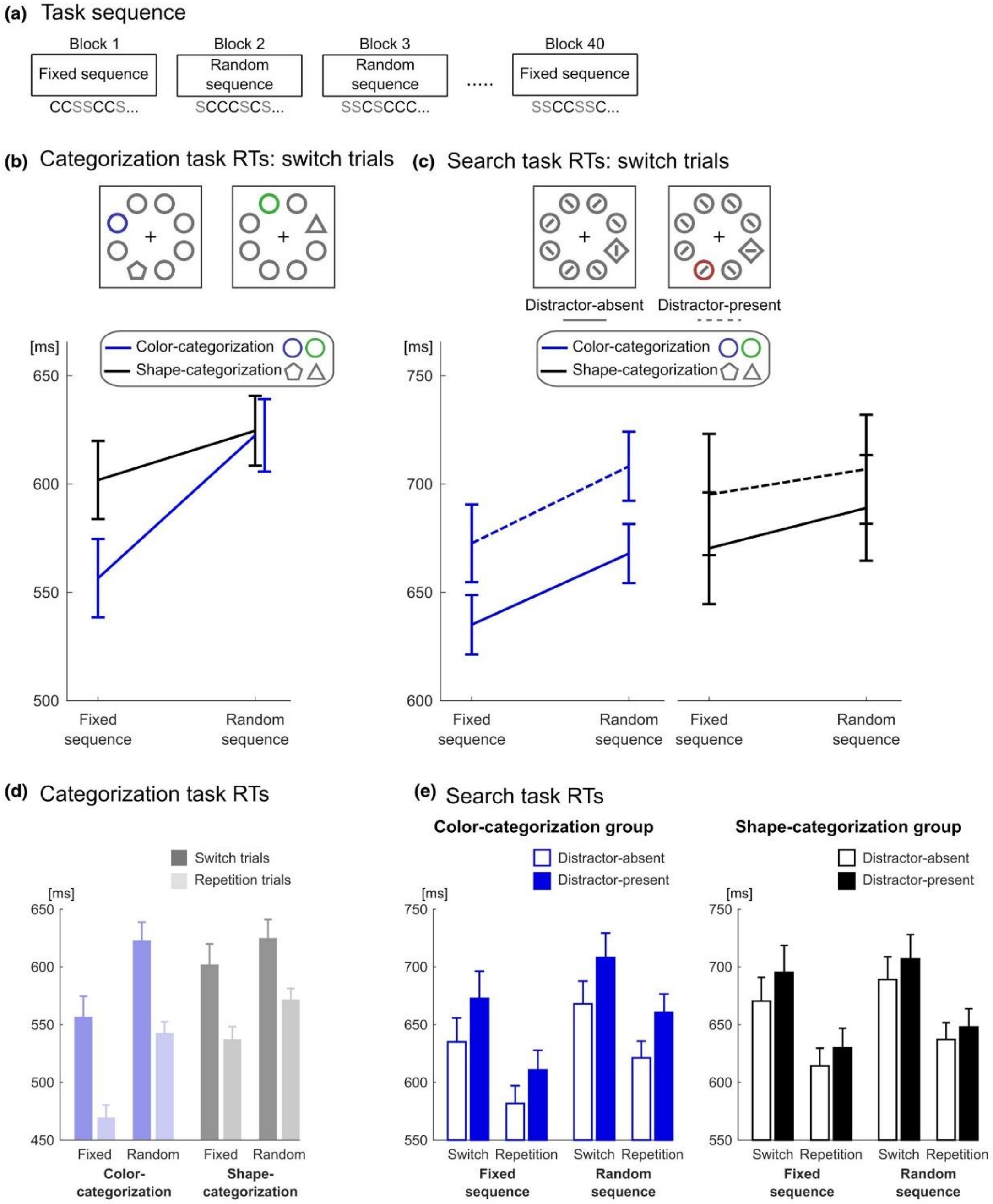


FIGURE 2 Legend on next page

2.2 | Stimulus and apparatus

Participants were seated in a comfortable chair in a dimly lit, electrically shielded and sound attenuated room and responded via a customizable keypad (Ergodex DX1) held on their lap. Two response buttons on the left half of the pad were used in the categorization task and two separate buttons on the right half of the pad were used in the search task. Participants used the thumb and ring finger of their left hand to respond during the categorization task and

FIGURE 2 (a) Schematic depiction of the two task sequences used in the experiment. Each rectangle represents one experimental block and each of the small letters below the rectangles represents one trial. Letters "C" represent categorization trials, and letters "S" represent search trials. Participants completed 20 blocks in each task sequence. In fixed-sequence blocks, categorization trials and the search task trials alternated in fixed sequences of two trials per task. In random-sequence blocks, trials of both tasks alternated in random order. Panels B and C are included for clarity with the focus on the switch trials and they are redundant to the complete presentation of the data depicted in panels D and E. (b) Mean response times in switch trials in the categorization task for the color-categorization (blue) and the shape-categorization group (black), separated for fixed and random task sequences. Error bars represent standard errors of the mean. (c) Mean response times in switch trials in the search task for the color-categorization (blue) and the shape-categorization group (black), separated for fixed and random task sequences. Solid lines show RTs for distractor-absent trials, dashed lines represent RTs for trials with an additional color distractor. Error bars represent standard errors of the mean. (d) Mean response times in the categorization task for the color-categorization (blue) and the shape-categorization group (gray), separated for fixed-sequence (left bars in each panel) and random-sequence blocks (right bars in each panel). Bars with darker colors show RTs for switch trials, bars with lighter colors show RTs for repetition trials. Error bars represent standard errors of the mean. (e) Mean response times in the search task in the color-categorization group (blue) and the shape-categorization group (black) in fixed-sequence (left panel) and random-sequence blocks (right panel). Filled bars show RTs for trials with an additional color distractor, unfilled bars show RTs for distractor-absent trials. Error bars represent standard errors of the mean

the index and middle finger of their right hand to respond during the search task. Task presentation was controlled via E-Prime 2.0 (Psychology Software Tools, Inc.) on a standard PC under Windows XP. Stimuli were presented on a 22″ LCD-TN screen (Samsung Syncmaster 2233) at a viewing distance of 100 cm. For auditory feedback, two stereo speakers were positioned behind the screen, each on one side (Logitech Z120 2.0).

In both tasks, the display consisted of eight objects of 2.3° visual angle placed equidistant from the screen center in a circular search array on a dark gray background (CIELAB coordinates with reference white point of D65: $L^* = 25.32$, $a^* = 0$, and $b^* = 0$; distance screen center to stimulus center: 6.3°; horizontal eccentricity: 5.7°). The display was not color-calibrated, but we measured and matched the luminance of the stimuli (~27–30 candela). In the categorization task, the display contained six neutral distractor stimuli (gray circles, $L^* = 46.44$, $a^* = 0$, and $b^* = 0$) and two unique objects (see Figure 1a). One unique object had a distinct color, either green ($L^* = 61.62$, $a^* = -56.72$, and $b^* = 51.06$) or blue ($L^* = 28.59$, $a^* = 40.83$, and $b^* = -65.28$). The other unique object had a distinct shape, either a triangle or a pentagon. This type of stimulus, which differs from its surroundings in a single featural dimension, is known as a singleton. The color and shape singletons were presented at any of eight equidistant locations with exactly one neutral distractor between them. All singleton combinations (blue/triangle, blue/pentagon, green/triangle, green/pentagon) were presented equally often in all possible locations.

In the search task, the target was a diamond-shaped singleton with a horizontal or vertical line inside (see Figure 1b). Neutral distractor stimuli were gray circles ($L^* = 46.44$, $a^* = 0$, and $b^* = 0$) that contained a gray oblique line tilted 45° to the left or right. In 40% of the search trials, the target was presented with seven neutral distractors (distractor-absent trials, Figure 1b). In the remaining 60% of trials, a color singleton in red ($L^* = 39.56$, $a^* = 49.69$, and $b^* = 29.59$, circular shape) with an embedded oblique line appeared with one neutral distractor separating it from the target (distractor-present trials, Figure 1b). Target and distractor appeared with equal likelihood in each of the eight stimulus positions and equally often in the same side of the visual field (distractor-present, same side) as on opposite sides (distractor-present, opposite sides). Each trial began with a centrally presented gray fixation cross (0.6° visual angle) 500 ms before the stimulus display, which remained on the screen throughout the trial.

It is common in the literature to isolate target and distractor processing in visual search by selectively presenting targets and distractors on the vertical meridian of the display (e.g., Hickey et al., 2009). When the target is presented on the vertical midline, this supports discrete identification of lateralized distractor processing in the ERP within a condition. However, there is an associated cost: if target and distractor positions are randomized in a dense search array, target-vertical trials occur rarely and ERPs are based on relatively few trials. With this in mind, we have not adopted this design in the current study, instead identifying variance in target and distractor processing through comparison of results across physically identical conditions. Within-condition ERPs are therefore based on many trials without the need for a long, exhausting experiment.

2.3 | Procedure

2.3.1 | General trial procedure

Categorization and search trials started with a fixation cross for 500 ms that was followed by the stimulus display for 200 ms. A blank screen with a central fixation cross was subsequently displayed for up to 1800 ms, indicating that participants should respond while maintaining fixation. A correct response within that time interval triggered the beginning of the inter-trial-interval (1000 ms). An erroneous or missing response led to acoustic feedback in form of a low buzzing tone.

2.3.2 | Feedback-guided learning phase

Participants started the experiment by completing a block of 64 categorization learning trials. Participants were informed that in each trial one stimulus would be different in color and another would be different in shape. They were asked to respond by pressing either the upper or lower response button with their left hand and told that errors were followed by a buzzing tone. They were not told which stimulus was assigned to which button press, or that only one dimension was response predictive. Instead, they had to use the acoustic feedback to find out which dimension was response relevant and how the two possible stimuli within that dimension were mapped to the response keys (see Kadel et al., 2017, for details). Participants in the color-categorization group learned to respond to color singletons and ignore shape singletons, pressing one key for a blue singleton and another for a green singleton. Participants in the shape-categorization group learned to respond to shape singletons and ignore color singletons, pressing one key for a triangle and another for a pentagon. The assignment of response buttons was varied across participants and response accuracy and speed were emphasized equally. In the first 32 trials of the learning phase, stimulus presentation was prolonged to 500 ms to facilitate learning. Participants proceeded to the next block when accuracy was >75%, otherwise they had to repeat the block. On average, participants performed 2.23 blocks of the learning categorization task (SD = 1.39) before shifting to the mixed practice phase.

2.3.3 | Mixed practice phase

This block was performed after the initial learning and combined 32 categorization learning task trials (as described above) with 32 search task trials in a random order. In search task trials, all participants responded to the orientation of the line embedded in the diamond shape target by pressing either the left or right response-board button with their right hand. Stimulus-response mapping was counterbalanced over participants within each of the color- and shape-categorization groups. In this phase of the experiment, stimuli were presented for 1000 ms in search trials in order to facilitate learning. As in the learning phase of the experiment, participants proceeded to the next block of trials when accuracy was >75%.

2.3.4 | Main experiment

The main experimental session was performed the next day and EEG was recorded throughout. Participants were informed that the task was to be performed in two types of experimental blocks. In random-sequence blocks, categorization and search trials were intermingled in a random, unpredictable order (with the limitation that no more than four trials of one task could follow each other). In fixed-sequence blocks, trials of the categorization and search task alternated in a fixed and predictable sequence of exactly two trials per task. The task trial sequence (fixed or random) was identified on the screen before the block started.

In total, participants completed 40 blocks of 64 trials each, 20 in each task sequence, 2560 trials in total, and 1280 trials in each of the categorization and search tasks. In the search task, 512 of the 1280 trials were distractor-absent trials, where in the remaining trials the distractor was presented either on the same side as the target (384 trials) or on the opposite side (384 trials). Immediate auditory feedback was given after incorrect responses. After errors, participants took a forced break of at least 8 s, and they were given performance feedback (RT and accuracy) after each block. Participants were prompted to take longer breaks of several minutes on two occasions.

2.4 | EEG recording

EEG was recorded from 64 Ag-AgCl active electrodes (actiCAP by Brain Products GmbH, Munich, Germany). Electrodes were placed according to the international 10–10 system. Vertical EOG (vEOG) was recorded from Fp1 and an electrode placed below the left eye, and horizontal EOG (hEOG) was recorded from electrode positions F9 and F10. Impedances were kept below 5 kΩ. All electrodes were referenced to FCz during recording and re-referenced offline to the average of all electrodes. The signal was recorded with a BrainAmp amplifier (Brain Products, Munich, Germany) at a sampling rate of 1000 Hz and high pass filtered at 0.016 Hz and a low pass filtered at 250 Hz (−3 dB cutoff, Butterworth filter, 30 dB/oct roll-off).

2.5 | Data analysis

2.5.1 | Behavioral data

The first trial of each block was rejected from analysis, as were trials with incorrect responses and trials with outlier RT (>2 *SD* from mean RT calculated separately for each participant and separately for each block and each task). This led to exclusion of 9.30% of trials in the shape-categorization group and 9.22% in the color-categorization group.

2.5.2 | EEG data

Brain Vision Analyzer (Brain Products, Munich, Germany), the Fieldtrip toolbox (Oostenveld et al., 2011) and custom scripts for Matlab R2019a (Mathworks, http://www.mathworks.com) were used for off-line EEG data processing.

Event-related potentials

EEG was segmented into 700-ms epochs time-locked to the display onset, including a 200-ms pre-stimulus baseline. Vertical EOG (vEOG) was calculated as the difference between Fp1 and the electrode placed below the left eye, and horizontal EOG (hEOG) was calculated as the difference between electrodes F9 and F10. The four channels were filtered using a low-pass filter of 35 Hz. Trials with eyeblink (vEOG > ±80 μV), or horizontal eye movements (hEOG > ±35 μV step criterion) within the first 350 ms after stimulus onset were excluded from analysis. Channels with activity > ±80 μV in the first 350 ms after stimulus onset in a trial were also excluded. The first trial of each block was rejected from analysis, as were trials with incorrect responses. Participants with less than 75% artifact-free trials were excluded from further analysis (8 participants). The remaining 32 participants had 88.1% artifact-free trials on average. In total, 12.0% of trials had to be excluded in the shape-categorization, and 11.8% in the color-categorization group.

To quantify the early Pd and N2pc in both categorization and search tasks, mean contralateral and ipsilateral activity in the ERP was calculated for electrodes PO7/PO8 and cross-conditional effect peaks were identified. A 40 ms window was centered on this peak latency and amplitude measures reflect the mean across this interval.

For the categorization task, the N2pc peak emerged at 224 ms. For the search task, Pd and N2pc measurements were separated across the conditions identified in Figure 4. In distractor-absent trials, the N2pc peaked at 246 ms (Figure 4a). When the target and distractor were in the same visual hemifield the early Pd peaked at 127 ms and the N2pc peaked at 236 ms (Figure 4b). When the target and distractor were in opposite visual hemifields, the positive-polarity early Pd expresses as a negative-polarity peak, because the ERP is locked to the location of the target stimulus (such that a positivity contralateral to the distractor emerges as a negativity contralateral to the target). In this condition, the early Pd peaked at 142 ms and the N2pc peaked at 294 ms (Figure 4c).

In addition to mean amplitude, onset latency of the N2pc component was analyzed in search task trials (distractor absent, distractor-present same side, distractor-present opposite sides) using a jackknife-based approach (Kiesel et al., 2008; Miller et al., 1998; Smulders, 2010). Conditional onset was defined as the point where 50% of maximum N2pc amplitude was reached (Kiesel et al., 2008). Relevant statistics are corrected for the jackknife procedure and this is identified with the subscript “c”.

Time-frequency analysis

Oscillatory activity was analyzed over a 3000 ms epoch beginning 2000 ms before display onset. Trials excluded from ERP analyses were also excluded from time-frequency analysis. Before performing time-frequency analysis, data were downsampled to 500 Hz. The spectral analysis of the zero-padded time series was performed using a Fast-Fourier transformation. Zero-padding was done using the “nextpow2” function which returns the smallest power-of-two larger than the length of the time series. The power spectrum of the EEG was computed within a 500 ms Hanning window which moved in steps of 30 ms, so that every bin represented data from 250 ms before and after the nominal latency. This analysis was performed for frequencies 2 to 32 Hz with a resolution of 1 Hz. Trials were sorted according to the factors task sequence (fixed vs. random sequence), and task repetition (task switch vs. task repetition), resulting in four conditions per participant. Power values of each frequency at each time point and electrode were averaged separately for each condition.

Because task-set reconfiguration was not required in repetition trials, our expectation was that differences in task-set reconfiguration should emerge as a difference in pre-stimulus alpha power between switch and repetition trials, but only for fixed-sequence blocks. In random-sequence blocks, there was no opportunity for participants to know when task repetitions would occur, and accordingly no opportunity for preparation.

To compute the difference in preparatory alpha between switch and repetition trials in fixed and random-sequence blocks, we contrasted power values in each time and frequency bin using [(switch−repetition)/(switch + repetition)] × 100 individually for each posterior channel (O1/2, PO7/8, PO3/4, P7/8, P5/6, P3/4, P1/2, Oz, POz and Pz). Next, power values were averaged over channels, separately for participants in each group. Finally, the power values of switch and repetition trials were forwarded to a statistical analysis based on a cluster-based permutation test with 5000 permutations. A cluster-defining threshold of $\alpha < .01$ was employed (corresponding to a critical t-value of 2.95; Maris & Oostenveld, 2007).

We used cluster-based permutation tests for the data in the frequency range of 6 to 32 Hz and in the time range of 800-ms pre-stimulus interval. Focusing the analysis on this range of data involved 27 frequency bins and 28 time bins in the analysis. Analysis was based on the average power spectrum of 17 posterior channels and compared the power spectrum of switch and repetition trials separately for fixed and random trial sequences. According to this, in each type of trial sequence and in each group, the labels of switch and repetition trials were permuted. In this analysis, a significant cluster indicated that the corresponding frequency power differed significantly between switch and repetition trials. To subsequently test whether this switch-vs-repetition effect differed in color- vs shape-categorization groups, the normalized power differences between switch and repetition were compared between the groups. In this analysis, the labels of color-categorization and shape-categorization were permuted. This analysis employed a cluster-based permutation test with 5000 permutations. A cluster-defining threshold of $\alpha < .05$ was employed (corresponding to a critical *t*-value of 2.04).

3 | RESULTS

A core motivating hypothesis for the study was that preparation would differ between shape- and color-categorization groups in task switch trials. Accordingly, we constrained the analysis of the ERP to switch trials. To provide a comprehensive description of participants' performance, RT analysis was conducted for all data.

3.1 | Categorization task

3.1.1 | Behavioral results

(See Figure 2b,d) RT and accuracy were analyzed in a 3-way ANOVA with a between-subject factor for categorization group (color-categorization group vs. shape-categorization group) and within-subject factors for task sequence (fixed vs. random sequence) and task repetition (task switch vs. task repetition). All reports in the results section identify mean plus/minus standard error of the mean ($M \pm SEM$).

A main effect of task sequence emerged, with faster responses in fixed-sequence blocks ($M = 541 \pm 10$ ms, $M = 590 \pm 9$ ms), $F(1,30) = 176.71$, $p < .001$, $\eta_p^2 = 0.85$. An additional main effect of task repetition was detected, with faster responses when the task repeated ($M = 530 \pm 7$ ms, $M = 601 \pm 12$ ms), $F(1,30) = 153.02$, $p < .001$, $\eta_p^2 = 0.84$. Task repetition interacted with task sequence: the benefit of task repetition was greater in fixed-sequence blocks (fixed-sequence: $\Delta M_{(\text{switch-rep})} = 76 \pm 6$ ms, random-sequence: $\Delta M_{(\text{switch-rep})} = 67 \pm 7$ ms), $F(1,30) = 7.32$, $p = .01$, $\eta_p^2 = 0.20$.

In line with the idea that participants in the color-categorization group would most benefit from the opportunity to prepare, task sequence interacted with categorization group: participants in the color-categorization group benefited from fixed task sequence more than did participants in the shape-categorization group (color-categorization group: $\Delta M_{(\text{rand-fix})} = 70 \pm 6$ ms, shape-categorization group: $\Delta M_{(\text{rand-fix})} = 29 \pm 4$ ms), $F(1,30) = 30.84$, $p < .001$, $\eta_p^2 = 0.51$). Similarly, task repetition interacted with categorization group: participants in the color-categorization group benefited from task repetition more than did participants in the shape-categorization group (color-categorization group: $\Delta M_{(\text{switch-rep})} = 84 \pm 10$ ms, shape-categorization group: $\Delta M_{(\text{switch-rep})} = 59 \pm 6$ ms), $F(1,30) = 4.55$, $p = .04$, $\eta_p^2 = 0.13$. Although participants in the color-categorization group responded nominally faster than participants in the shape-categorization group ($M = 548 \pm 13$ ms, $M = 584 \pm 13$ ms), this effect failed to reach significance, $F(1,30) = 3.58$, $p = .07$, $\eta_p^2 = 0.11$. No other effects emerged (all *p*s $> .1$).

The only reliable effect on accuracy was a main effect of task repetition ($M_{\text{repetition}} = 98.4 \pm 0.2\%$ vs. $M_{\text{switch}} = 96.3 \pm 0.5\%$), $F(1,30) = 40.18$, $p < .001$, $\eta_p^2 = 0.57$.

3.1.2 | ERP results

(See Figure 3) Focusing on the switch trials, the N2pc was analyzed in a 2-way ANOVA with between-subject factor for categorization group and within-subject factor for task sequence. Figure 3 further separates the data as a function of the location of the non-predictive singleton, but statistical analysis was collapsed across this factor. As evident in Figure 3, color singletons create an early positive-polarity effect in the lateral ERP. This early lateral positivity emerges contralateral to the location of the color singleton for both color-categorization and shape-categorization groups without differing between these groups. This appears to reflect the "positivity posterior contralateral" component (PPC), which is thought to reflect stimulus salience and does not vary as a function of whether an eliciting stimulus is a target or distractor (Corriveau et al., 2012). Consistent with the idea that preparation would improve attentional resolution of the target, analysis of the N2pc identified a main effect of task sequence, with the N2pc larger in fixed-sequence blocks ($M = -0.96 \pm 0.21$ µV, $M = -0.73 \pm 0.21$ µV), $F(1,30) = 5.73$, $p = .02$, $\eta_p^2 = 0.16$. No other effects emerged (all *p*s $> .1$).

3.2 | Search task

3.2.1 | Behavioral results

(See Figure 2c,e) RT and accuracy were analyzed in a 4-way ANOVA with a between-subject factor for categorization group (color-categorization group vs. shape-categorization group) and within-subject factors for distractor-presence (distractor present vs. absent), task sequence (fixed vs. random sequence), and task repetition (task switch vs. task repetition).

In analysis of RT, a main effect of distractor-presence emerged, with slower responses when the distractor was present ($M = 640 \pm 12$ ms, $M = 667 \pm 13$ ms), $F(1,30) = 84.09$, $p < .001$, $\eta_p^2 = 0.74$. An additional main effect of task sequence emerged, with faster responses in fixed-sequence blocks ($M = 639 \pm 13$ ms, $M = 667 \pm 12$ ms), $F(1,30) = 44.31$, $p < .001$, $\eta_p^2 = 0.60$. The main effect of task repetition was also significant, with faster responses in task repetition trials ($M = 625 \pm 11$ ms, $M = 681 \pm 15$ ms), $F(1,30) = 68.37$, $p < .001$, $\eta_p^2 = 0.70$.

Categorization group interacted with distractor-presence: the distractor cost was larger in the color-categorization group ($\Delta M = 37 \pm 5$ ms, $\Delta M = 17 \pm 3$ ms), $F(1,30) = 10.82$, $p = .003$, $\eta_p^2 = 0.27$. The history of selecting color during the categorization task appears to have increased sensitivity to color during the search task.

Categorization group also interacted with task sequence: the propensity toward faster responses in fixed-sequence blocks was accentuated in the color-categorization group (color-categorization group: $\Delta M_{\text{(rand-fix)}} = 39 \pm 7$ ms, shape-categorization group: $\Delta M_{\text{(rand-fix)}} = 18 \pm 5$ ms), $F(1,30) = 6.29$, $p = .02$, $\eta_p^2 = 0.17$. This suggests increased preparation in this group, who had to switch task sets between trial types. Note that even though the color-categorization group responded numerically faster than the shape-categorization group in the fixed-sequence blocks ($M_{\text{color-categorization}} = 625 \pm 19$ ms, $M_{\text{shape-categorization}} = 652 \pm 19$ ms, $t(30) = 1.04$, $p = .30$), the distractor cost remained marginally larger ($\Delta M_{\text{color-categorization}} = 33 \pm 5$ ms, $\Delta M_{\text{shape-categorization}} = 20 \pm 4$ ms, $t(30) = 2.05$, $p = .05$).

Task sequence interacted with task repetition: the benefit of task repetition was greater in fixed-sequence blocks than in random-sequence blocks ($\Delta M_{\text{(switch-rep)}} = 59 \pm 7$ ms, $\Delta M_{\text{(switch-rep)}} = 51 \pm 6$ ms), $F(1,30) = 6.57$, $p = .02$,

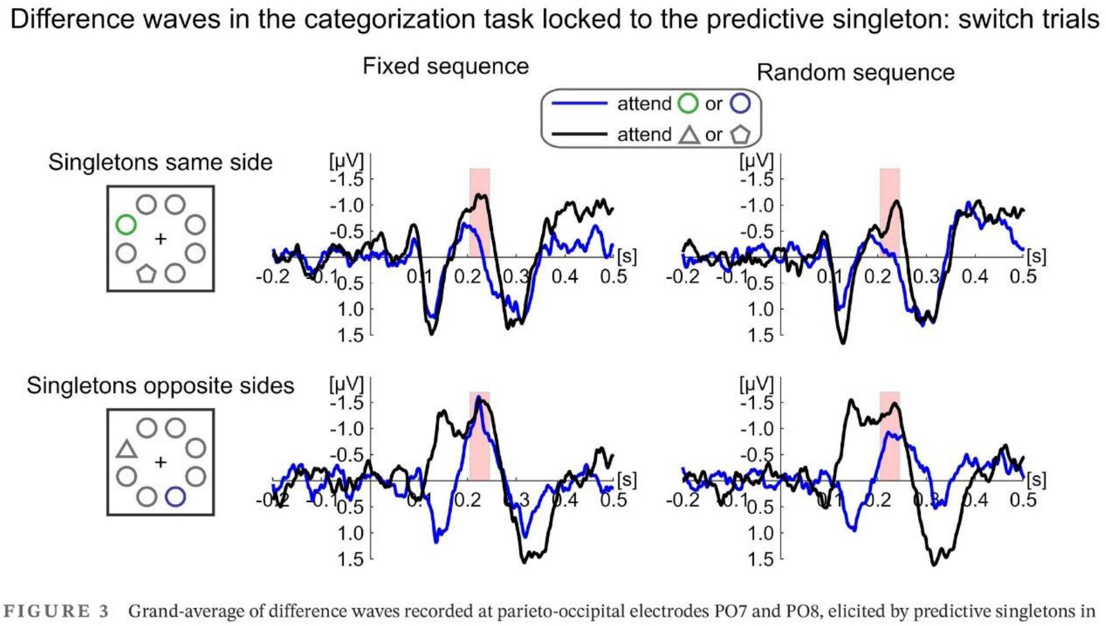


FIGURE 3 Grand-average of difference waves recorded at parieto-occipital electrodes PO7 and PO8, elicited by predictive singletons in switch trials in the categorization task, locked to the location of the color singleton in the color-categorization group (blue lines) or locked to the location of the shape singleton in the shape-categorization group (black lines). The upper panels represent the waveforms when singletons appear on the same side and the lower panels represent the waveforms when singletons appear on the opposite sides for fixed (left panels) and random-sequence blocks (right panels). For illustration purposes, EEG waveforms were filtered using a low-pass Butterworth filter with high cutoff frequency of 35 Hz (12 dB/oct)

$\eta_p^2 = 0.18$. Task repetition also interacted with distractor cost: the distractor cost was smaller when the task was repeated ($\Delta M = 24 \pm 4$ ms, $\Delta M = 30 \pm 3$ ms), $F(1,30) = 8.40$, $p = .007$, $\eta_p^2 = 0.22$.

A marginal three-way interaction between distractor-presence, task sequence, and categorization group emerged: participants showed a numerically smaller distractor cost in fixed-sequence blocks, but only in the color-categorization group (color-categorization group: $\Delta M_{\text{fixed}} = 33 \pm 5$ ms, $\Delta M_{\text{random}} = 40 \pm 6$ ms; shape-categorization group: $\Delta M_{\text{fixed}} = 20 \pm 4$ ms, $\Delta M_{\text{random}} = 14 \pm 3$ ms), $F(1,30) = 3.89$, $p = .058$, $\eta_p^2 = 0.11$.

No other effects on RT emerged ($ps > .1$) and the only reliable effect on accuracy was an improvement in repetition trials ($M = 96.6 \pm 0.4\%$, $M = 95.7 \pm 0.6\%$), $F(1,30) = 5.21$, $p = .03$, $\eta_p^2 = 0.15$.

3.2.2 | ERP results. Distractor-absent trials (Figure 4a)

Target-elicited N2pc

Focusing on the switch trials, the N2pc was analyzed with a 2-way ANOVA with a between-subjects factor for categorization group and within-subject factor for task sequence. This identified a trend toward an interaction of categorization group and task sequence, with the effect of task sequence more pronounced in the color-categorization group ($M_{\text{fixed}} = -1.16 \pm 0.30$ µV, $M_{\text{random}} = -0.78 \pm 0.28$ µV) than in the shape-categorization group ($M_{\text{fixed}} = -1.47 \pm 0.30$ µV, $M_{\text{random}} = -1.58 \pm 0.28$ µV), $F(1,30) = 3.27$, $p = .08$, $\eta_p^2 = 0.10$. No other effects emerged ($ps > .1$). N2pc onset did not reliably vary in any analysis ($ps > .1$).

3.2.3 | ERP results. Distractor-present trials: target and distractor in same hemifield (Figure 4b)

Distractor-elicited early Pd

We focused on switch trials in analysis of the early Pd. A 2-way ANOVA with a between-subject factor for categorization group and a within-subject factor for task sequence identified a main effect of categorization group: early Pd was larger in the shape-categorization group ($M = 0.98 \pm 0.14$ µV, $M = 0.57 \pm 0.14$ µV), $F(1,30) = 4.36$, $p = .045$, $\eta_p^2 = 0.13$. A main effect of task sequence also emerged, with the Pd larger in fixed-sequence blocks ($M = 0.99 \pm 0.14$ µV, $M = 0.57 \pm 0.12$ µV), $F(1,30) = 5.25$, $p = .03$, $\eta_p^2 = 0.15$, as well as a trend toward an interaction of categorization group and task sequence, with the effect of task sequence more pronounced in the shape-categorization group ($M_{\text{fixed}} = 1.36 \pm 0.20$ µV, $M_{\text{random}} = 0.60 \pm 0.18$ µV) than in the color-categorization group ($M_{\text{fixed}} = 0.61 \pm 0.20$ µV, $M_{\text{random}} = 0.53 \pm 0.18$ µV), $F(1,30) = 3.36$, $p = .08$, $\eta_p^2 = 0.10$. Separate comparisons between the early Pd in fixed and in random-sequence blocks for each group showed that the marginal interaction of categorization group and task sequence was driven by the shape-categorization group ($t(15) = 3.58$, $p = .003$) rather the color-categorization group ($t(15) = 0.28$, $p = .78$).

Target-elicited N2pc

Focusing on the switch trials, the N2pc was analyzed with a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence. This identified a significant interaction of categorization group with task sequence, with the effect of task sequence more pronounced in the color-categorization group ($M_{\text{fixed}} = -1.18 \pm 0.32$ µV, $M_{\text{random}} = -.69 \pm 0.30$ µV) than in the shape-categorization group ($M_{\text{fixed}} = -1.19 \pm 0.32$ µV, $M_{\text{random}} = -1.48 \pm 0.30$ µV), $F(1,30) = 5.77$, $p = .02$, $\eta_p^2 = 0.16$. No other effects emerged ($ps > .1$) and there was no effect on N2pc onset latency ($ps > .1$).

3.2.4 | ERP results. Distractor-present trials: target and distractor in opposite hemifield (Figure 4c)

Distractor-elicited early Pd

As noted above, the Pd in this condition expresses as a negativity contralateral to the target (and thus a positivity contralateral to the distractor). Focusing on the switch trials, a 2-way ANOVA with a between-subject factor for categorization group and a within-subject factor for task sequence identified a significant interaction of categorization group with task sequence, with the effect of task sequence more pronounced in the shape-categorization ($M_{\text{fixed}} = -1.31 \pm 0.22$ µV, $M_{\text{random}} = -0.80 \pm 0.18$ µV) than in the color-categorization group ($M_{\text{fixed}} = -0.54 \pm 0.22$ µV, $M_{\text{random}} = -0.78 \pm 0.18$ µV), $F(1,30) = 6.39$, $p = .02$, $\eta_p^2 = 0.18$. This significant interaction was further analyzed by comparing the early Pd in fixed and random-sequence blocks for each group using two dependent sample t tests. This analysis showed that the amplitude of the early Pd significantly differed between fixed and random-sequence blocks, but only for the shape-categorization group (shape-categorization: $t(15) = 2.35$, $p = .03$; color-categorization: $t(15) = 1.20$, $p = .25$). There were no other significant effects on the early Pd (all $ps > .1$). Further analysis of the Pd—collapsed across the results illustrated in Figure 4b,c—is described below.

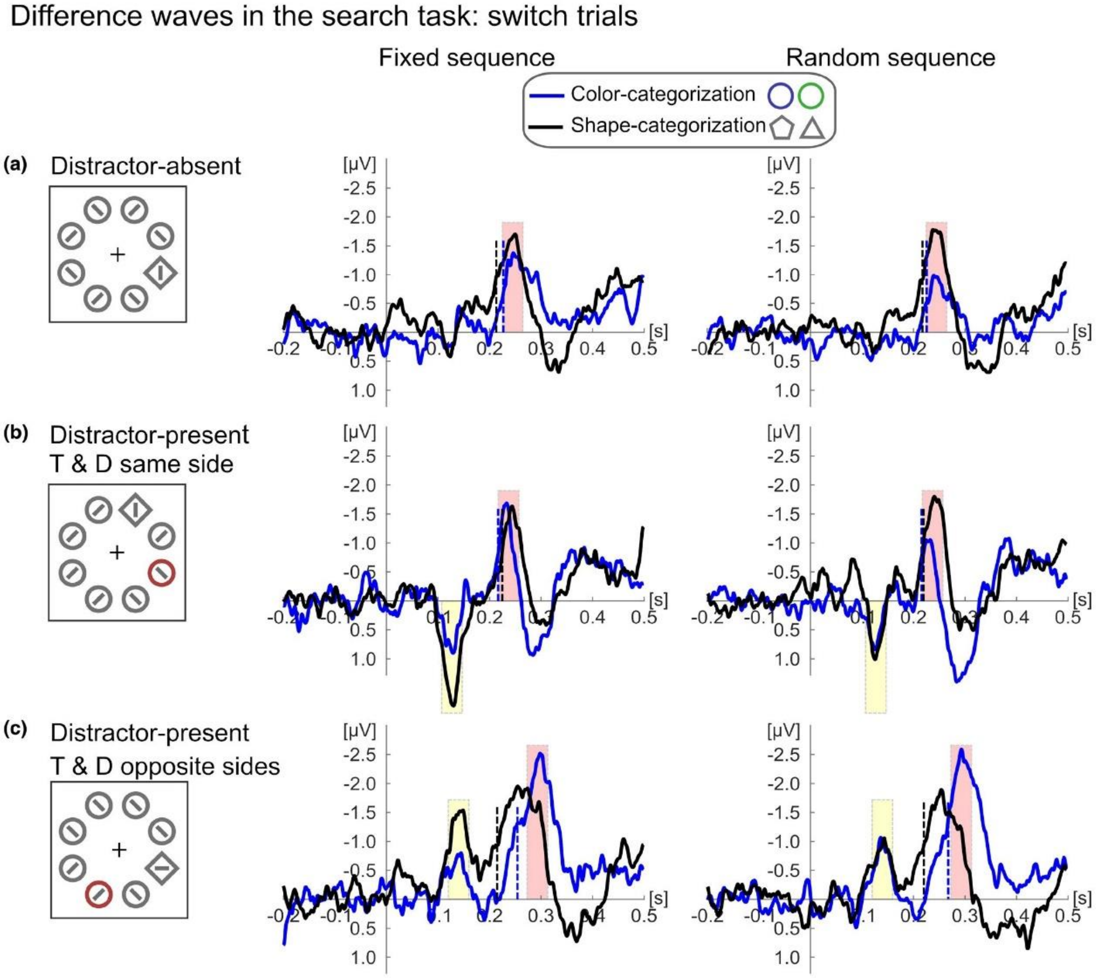


FIGURE 4 ERP difference waves computed from contra- minus ipsilateral waveforms recorded at parieto-occipital electrodes PO7 and PO8 in switch trials in the search task: (a) ERPs in distractor-absent trials, (b) ERPs in trials with target and distractor presented on the same side of the visual field and (c) ERPs in trials with target and distractor presented on opposite sides of the visual field. ERPs are visualized separately for fixed (left panels) and random-sequence blocks (right panels). Blue lines represent difference waves of the color-categorization group; black lines represent difference waves of the shape-categorization group. The epochs marked in yellow represent the early Pd component and the epochs marked in red represent the N2pc component. Vertical dotted lines represent the time point at which 50% of the maximum amplitude was reached. For illustration purposes, time series were filtered using a low-pass Butterworth filter with high cutoff frequency of 35 Hz (12 dB/oct)

Target-elicited N2pc

Focusing on switch trials, a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence identified a trend to an effect of categorization group: the N2pc amplitude was numerically larger in the color-categorization group ($M = -2.20 \pm 0.36\ \mu V$) than in the shape-categorization group ($M = -1.23 \pm 0.36\ \mu V$), though this did not reach significance, $F(1,30) = 3.72$, $p = .06$, $\eta_p^2 = 0.11$. No other effects emerged (all $ps > .1$). The N2pc emerged earlier in the shape-categorization group ($M_{\text{shape-categorization}} = 218 \pm 0.8$ ms, $M_{\text{color-categorization}} = 261 \pm 0.8$ ms). When jacknife latency measures were submitted to a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence, a main effect of categorization group emerged, $F_c(1,30) = 7.25$, $p = .01$, $\eta_p^2 = 0.98$, all other $ps > .1$.

3.2.5 | ERP results. Early Pd collapsed across "Target and distractor in same hemifield" (Figure 4b) and "Target and distractor in opposite hemifield" (Figure 4c) conditions

To gain statistical power, we additionally analyzed the early Pd elicited in switch trials across the "target and distractor in same hemifield" and "target and distractor in opposite hemifield" conditions. Because the early Pd expressed as a positivity when target and distractor were in one hemifield, but as a negativity when these stimuli were located contralateral to one another, this analysis was based on rectified polarity as measured at its cross-conditional peak.

A 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence identified a main effect of categorization group, with the Pd larger in the shape-categorization group ($M = 1.02 \pm 0.13$ μV, $M = 0.62 \pm 0.13$ μV), $F(1,30) = 4.53$, $p = .04$, $\eta_p^2 = 0.13$, and a main effect of task sequence ($M_{\text{fixed}} = 0.96 \pm 0.12$ μV, $M_{\text{random}} = 0.68 \pm 0.10$ μV), $F(1,30) = 5.31$, $p = .03$, $\eta_p^2 = 0.15$.

Importantly, categorization group interacted with task sequence: the difference between fixed and random-sequence blocks was larger for participants in the shape-categorization group (shape-categorization group: $M_{\text{fixed}} = 1.33 \pm 0.17$ μV vs. $M_{\text{random}} = 0.70 \pm 0.14$ μV, color-categorization group: $M_{\text{fixed}} = 0.58 \pm 0.17$ μV vs. $M_{\text{random}} = 0.66 \pm 0.14$ μV), $F(1,30) = 8.79$, $p = .006$, $\eta_p^2 = 0.23$. The stimulus-triggered suppression indexed in the early Pd was thus larger in the shape-categorization group, when the fixed task sequence gave the opportunity for quick stimulus-triggered suppression when the stimulus appeared. Finally, separate comparisons between the early Pd in fixed and in random-sequence blocks for each group showed that the interaction of categorization group and task sequence was solely driven by the shape-categorization group ($t(15) = 4.59$, $p < .001$), and not by the color-categorization group ($t(15) = 0.40$, $p = .69$).

3.2.6 | Time-frequency results (Figure 5)

To index pre-stimulus preparation we contrasted oscillatory power in switch trials with oscillatory power in repetition trials. This was separately achieved for fixed and random-sequence blocks for each of the color-categorization (Figure 5a) and shape-categorization groups (Figure 5b).

In fixed-sequence blocks, participants in the color-categorization group showed less power in posterior alpha (8–14 Hz) in the −470−−800 interval in switch compared to repetition trials ($p < .01$; mean power spectrum in the significantly different bins: $M_{\text{switch}} = 9.65 \pm 2.52$ μV^2, $M_{\text{repetition}} = 10.72 \pm 2.70$ μV^2; Figure 5a, upper panels). No corresponding effect emerged in random-sequence blocks (Figure 5a, lower panels).

This pattern did not emerge with the same strength in the shape-categorization group (Figure 5b). In fixed-sequence blocks, participants in the shape-categorization group showed less power in posterior alpha (12–14 Hz) in the −530−−800 interval in switch compared to repetition trials ($p < .01$; mean power spectrum in the significantly different bins: $M_{\text{switch}} = 7.25 \pm 3.01$ μV^2, $M_{\text{repetition}} = 7.86 \pm 3.20$ μV^2; Figure 5b, upper panels). No corresponding effect emerged in random-sequence blocks (Figure 5b, lower panels). To contrast the groups, we compared the normalized switch-vs-repetition effect using cluster-based permutation tests (Figure 5c). When comparing pre-stimulus power between switch and repetition trials in the categorization task, no significant difference in the range of alpha-band was observed.

4 | DISCUSSION

This study investigated the relation of two potentially conflicting influences on attentional selection, namely proactive top-down control and selection history. The primary motivating question was whether participants would adjust proactive attentional control to compensate for an attention bias resulting from individual selection history. The study was designed to identify the specific mechanisms that might support this kind of control.

Participants performed a combination of two intermingled visual tasks, a categorization task and a search task. In the categorization task, they were presented with stimuli arrays containing a shape singleton and a color singleton (Figure 1a). Half of the participants—the shape-categorization group—reported the shape of the shape singleton, whereas the other half—the color-categorization group—reported the color of the color singleton. In the search task, all participants searched for a shape singleton in an array that sometimes contained a task-irrelevant color singleton (Theeuwes, 1991).

Preparing for a new task after having performed a different task requires an updating process known as *task-set reconfiguration* (e.g., Karayanidis et al., 2010; Longman et al., 2013; Meiran et al., 2008). Although both groups in our experiment had to reconfigure their task set (e.g., shift from categorization to search, respond with different effectors), switching between tasks was more complex for the color-categorization group. These participants had to search for color singletons in the categorization task and ignore shape singletons, but search for shape singletons in the search task and ignore color singletons. Participants in the shape-categorization group had it easier: they always searched for shape singletons and ignored color singletons.

Based on prior work, we expected that participants in the color-categorization group would show a strong attentional bias toward the color singleton in the search task, reflecting the influence of selection history and the cost of having to switch attentional templates

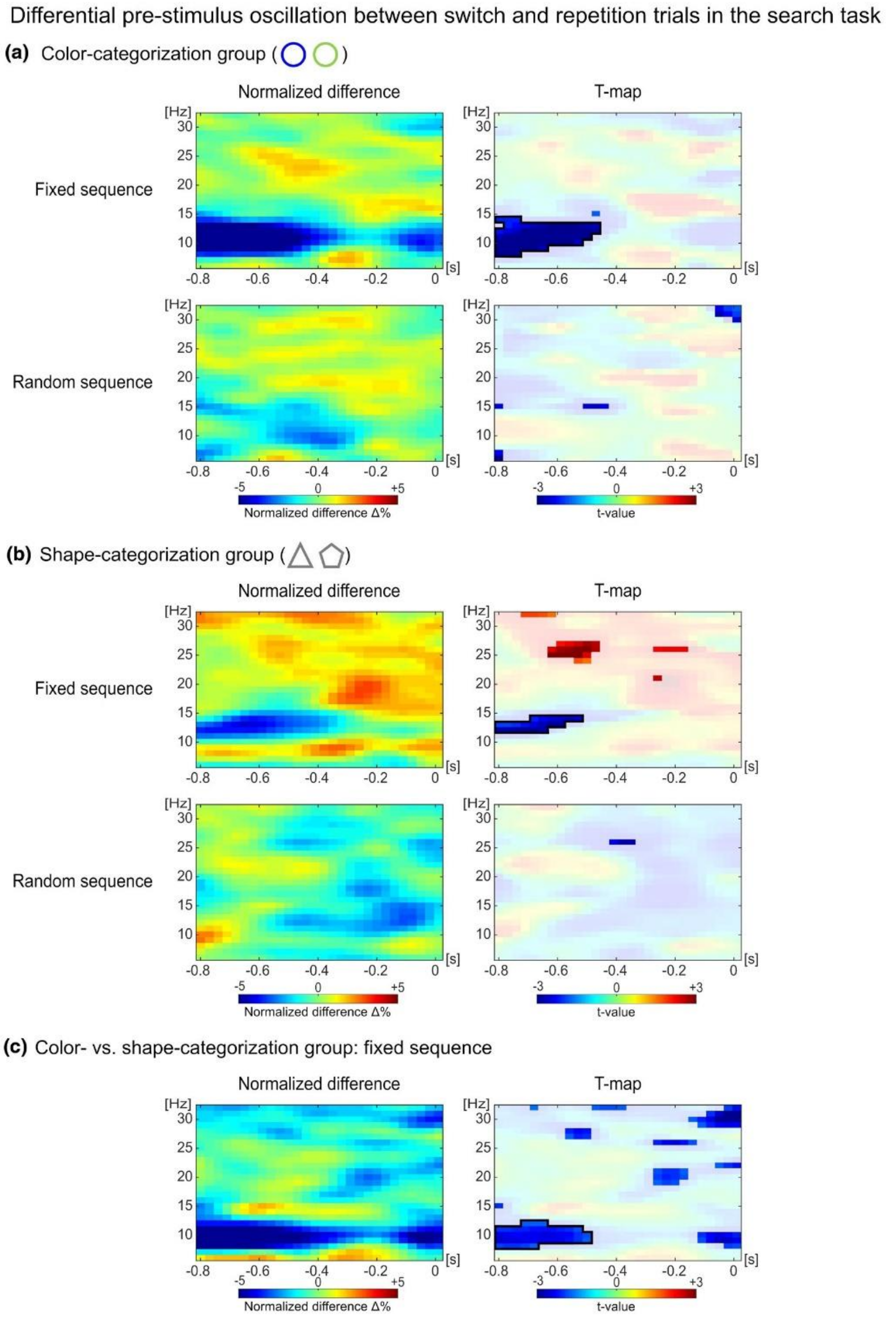


FIGURE 5 (a and b) Differential pre-stimulus oscillation between switch and repetition trials in the color-categorization (a) and the shape-categorization group (b) in fixed (upper panels) and random-sequence blocks (lower panels). Left graphs show normalized differences in pre-search power between switch and repetition trials at posterior channels (pool of O1/2, PO7/8, PO3/4, P7/8, P5/6, P3/4, P1/2, Oz, POz and Pz). Normalized differences were calculated as $[(\text{switch}-\text{repetition})/(\text{switch}+\text{repetition})] \times 100$ for each time (28 bins) and frequency (27 bins) point for each channel. Right panels show *t*-values, calculated by cluster-based permutation tests. For illustration purposes, bins in the T-maps with $p > .01$ were plotted with less opacity. (c) Comparison of normalized differences in pre-search power between switch and repetition trials in the color-categorization group with that in the shape-categorization group in fixed-sequence blocks. The left graph represents between-group differences of the averaged power over 17 posterior channels. The right panel shows *t*-values calculated by cluster-based permutation tests using independent *t* test. For illustration purposes, bins in the T-maps with $p > .05$ were plotted with less opacity

(Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017). The question was whether participants would be able to establish control over this residual attentional bias and how this control would be mechanistically implemented. To give participants the opportunity to establish control, in some experimental blocks the categorization and search tasks alternated in fixed sequence, so that participants were afforded the opportunity to prepare (Figure 2a). We expected to find that the color-categorization group would use this opportunity more than would the shape-categorization group because their task required greater control.

As expected, results showed that the color-categorization group was more sensitive to the distractor during search. Importantly, the color-categorization group also showed behavioral and electrophysiological evidence of greater preparation. In behavior, this expressed as a RT benefit in fixed-sequence blocks that was stronger for the color-categorization group (Figure 2b,c). In particular, distractor costs in fixed-sequence blocks nominally reduced in the color-categorization group (though this did not reach statistical significance; Figure 2c). In electrophysiology, enhanced preparation was apparent in posterior alpha oscillations. When fixed task sequence allowed them to prepare, both color-categorization and shape-categorization groups showed a reduction of pre-stimulus oscillatory power in the alpha band that was stronger before task-switch trials (Figure 5a,b). However, this effect was substantially larger in the color-categorization group, consistent with the idea that these participants prepared more before the task switch than did the shape-categorization group (Figure 5c).

Preparation thus appears indexed in pre-stimulus posterior alpha and had an impact on post-stimulus behavior. To gain insight on the specific selective mechanisms through which preparation facilitated behavior, we looked to the early Pd and N2pc components of the post-stimulus ERP. The early Pd is known to index rapid, stimulus-triggered distractor suppression (Gaspar & McDonald, 2014; Sawaki & Luck, 2013; Weaver et al., 2017; van Zoest et al., 2021), whereas the N2pc tracks attentional resolution of target features (Luck & Hillyard, 1994a).

4.1 | Preparation in fixed task sequence reduces the need for post-stimulus suppression

Strikingly, enhanced preparation in the color-categorization group was associated not with an increase in early Pd, but with its reduction. That is, the shape-categorization group showed a larger distractor-elicited early Pd in task-switch trials within fixed-sequence blocks than was observed for the color-categorization group (Figure 4b,c). Our interpretation of this pattern is that the preparation tracked in posterior alpha did not facilitate post-stimulus distractor suppression. Rather, this preparation led to a reduction in need for such suppression (cf. van Moorselaar & Slagter, 2020; van Zoest et al., 2021). That is, pre-stimulus suppression led to a situation where the color singleton, when it appeared, had less salience, and therefore required less stimulus-triggered suppression. This could reflect the silencing of feature channels in visual cortex.

It is important to note that an alternative interpretation of this data pattern is available. The early Pd in fixed-sequence blocks may not be reduced in the color-categorization group, but rather increased in the shape-categorization group. This could indicate that the shape-categorization group did not prepare prior to task switches to the same degree as the color-categorization group. As a result, they relied more heavily on stimulus-triggered distractor suppression in order to limit the disruptive influence of the color singleton, resulting in a prominent Pd in fixed-sequence switch trials (Figure 4b,c). Why might participants in the shape-categorization group use post-stimulus suppression when there was the opportunity for pre-stimulus suppression? One possibility is that stimulus-triggered, reactive distractor suppression is less effortful than pre-stimulus maintenance of attentional set. If participants in the shape-categorization group were to employ pre-stimulus attentional set, they would have had to switch sets very commonly in our task—at least once every two trials. The shape-categorization group may have not engaged in this effortful task-switching, instead relying on reactive control (Braver, 2012), and thus the stimulus-triggered suppression reflected in early Pd. Critically, both interpretations offered here share the notion that pre-stimulus preparation in the color-categorization group resulted in a decrease in need for stimulus-triggered distractor suppression, relative to the shape-categorization group.

The current results add to a growing body of work showing that goal-oriented top-down control mechanisms are especially efficient in guiding attention when they can be instantiated and fine-tuned to current task requirements *before* stimulus onset (Amit et al., 2019; Burra & Kerzel, 2013; Nessler et al., 2012). When participants were faced with a challenging task, they employed such pre-stimulus preparation in an attempt to best optimize their performance.

For example, Liu et al. (2016) found that the N2pc in a perceptually difficult discrimination task was larger when that task was presented predictably and in isolation than when it was intermixed with other difficulty levels of the same task. Similarly, Burra and Kerzel (2013) showed that blockwise predictability of the exact target feature not only increased the target-elicited N2pc during search, but also reduced the distractive potential of a simultaneously presented additional singleton distractor. They argued that observers had used the predictable task blocks to adjust feature selection in an anticipatory, top-down manner. The present study supports and extends this interpretation with neural evidence for predictability-specific task preparation. This is not trivial, as participants in our study were neither instructed nor required to prepare proactively for the upcoming task, and results from the shape-categorization group show that participants could adopt reactive control processes to support task completion (Braver, 2012).

4.2 | Proactive control in predictable versus unpredictable task switching

Our results show a reduction of posterior alpha power that seems to track the establishment of task preparation and the need for changes in attentional set. Several previous studies have reported alpha modulations in paradigms in which observers switched their attention between different visual or sensory tasks. For example, Gladwin and de Jong (2005) found that pre-stimulus posterior alpha decreased in power when participants were cued to switch between auditory and visual tasks, and Foxe et al. (2014) found similar results when the switch was voluntary. Poljac and Yeung (2014) found the same alpha decrease when voluntary task switches were made between unimodal visual tasks. Cooper et al. (2016) have recently investigated the nature of alpha reduction elicited by cues indicating the need for task switching across variety of paradigms (oddball, go/nogo and task switching). Results suggest that reductions in alpha power may reflect a working memory/rule updating process. Although our study did not use a cue to indicate task switch or repetition, working memory processes and rule updating might have played a role here, as participants had to memorize the trial sequence to prepare for the upcoming trial in fixed-sequence blocks.

Interestingly, pre-stimulus alpha-band power in the categorization task did not differ between switch and repetition trials in fixed-sequence blocks in either of the color-categorization or shape-categorization groups. This further suggests that the pre-stimulus alpha-band modulation observed in fixed-sequence blocks in the search task is probably specific to the setting-up of proactive color suppression, rather than establishment of any general template supporting task completion.

4.3 | The functional significance of early positive-polarity laterality: PPC versus early Pd

What we have referred to as the early Pd in consideration of results from the search task is very similar in latency and polarity to the PPC we identify in the categorization task. That is, in results from both the categorization and search tasks, the ERP shows a strong positive deflection contralateral to the color singleton (Figures 3 and 4), but we label this positive component “PPC” in interpreting the categorization results, but “early Pd” in interpreting the search results. In using these labels, we are attempting to define distinct nomenclature that reflects differences in function. The PPC has been convincingly linked to processing of raw stimulus salience (Corriveau et al., 2012; Pomerleau et al., 2014). Consistent with this, the PPC observed in the categorization task consistently emerges contralateral to the color singleton in all conditions; it is sensitive to the raw physical salience of the color singleton, but not to changes in task context. In contrast, the early Pd has been linked to distractor suppression (Weaver et al., 2017; van Zoest et al., 2021). In line with this idea, the early Pd observed in the search task varies as task context changes the need for selective processing and distractor handling (though physical stimulation remains identical). The PPC and early Pd are therefore distinct in their functional significance. Importantly, it seems likely to us that the positive-polarity effect observed in the search task is composed, in part, of a PPC elicited by the raw physical salience of the color distractor. However, because the PPC is defined by its insensitivity to task context, the fact that the early positivity is sensitive to experimental manipulations (when physical stimulation remains identical) identifies the additional emergence of early Pd.

5 | CONCLUSION

The current results demonstrate that participants will proactively tune their attentional control settings to an upcoming task, and that this will reduce the attentional bias created by prior task set and selection history. However, such proactive control is not necessarily sufficient to compensate for these biases. In these results, participants showed a propensity to be strongly distracted by previous task-relevant objects even in spite of neural and behavioral evidence of their preparation for the appearance of these stimuli. Strategic attentional control thus plays a role in defining attentional prioritization, but does not necessarily have the power to negate the influence of residual attentional biases created by earlier experience.

ACKNOWLEDGMENT

This research was supported by the Deutsche Forschungsgemeinschaft (German Research Foundation; SFB/TRR 135, project number 222641018, TP B3, and IRTG 1901). CH is supported by a European Research Council Horizon 2020 Starting Grant (INSENSE 804360). Open Access funding enabled and organized by Projekt DEAL.

AUTHOR CONTRIBUTIONS

Hossein Abbasi: Formal analysis; Methodology; Software; Visualization; Writing—original draft. **Hanna Kadel:** Conceptualization; Data curation; Formal analysis; Methodology; Writing—original draft. **Clayton Hickey:** Methodology; Validation; Writing—review & editing. **Anna Schubö:** Conceptualization; Funding acquisition; Methodology; Resources; Supervision; Writing—review & editing.

ORCID

Hossein Abbasi https://orcid.org/0000-0002-9515-4859

REFERENCES

Amit, R., Abeles, D., Carrasco, M., & Yuval-Greenberg, S. (2019). Oculomotor inhibition reflects temporal expectations. *NeuroImage*, *184*, 279–292. https://doi.org/10.1016/j.neuroimage.2018.09.026

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(25), 10367–10371. https://doi.org/10.1073/pnas.1104047108

Ansorge, U., Kiss, M., Worschech, F., & Eimer, M. (2011). The initial stage of visual selection is controlled by top-down task set: New ERP evidence. *Attention, Perception, & Psychophysics*, *73*(1), 113–122. https://doi.org/10.3758/s13414-010-0008-3

Antonov, P. A., Chakravarthi, R., & Andersen, S. K. (2020). Too little, too late, and in the wrong place: Alpha band activity does not reflect an active mechanism of selective attention. *NeuroImage*, *219*, e117006. https://doi.org/10.1016/j.neuroimage.2020.117006

Arita, J. T., Carlisle, N. B., & Woodman, G. F. (2012). Templates for rejection: Configuring attention to ignore task-irrelevant features. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(3), 580–584. https://doi.org/10.1037/a0027885

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10.1016/j.tics.2012.06.010

Battistoni, E., Stein, T., & Peelen, M. V. (2017). Preparatory attention in visual cortex. *Annals of the New York Academy of Sciences*, *1396*(1), 92–107. https://doi.org/10.1111/nyas.13320

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Burra, N., & Kerzel, D. (2013). Attentional capture during visual search is attenuated by target predictability: Evidence from the N2pc, Pd, and topographic segmentation. *Psychophysiology*, *50*(5), 422–430. https://doi.org/10.1111/psyp.12019

Busch, N. A., Dubois, J., & VanRullen, R. (2009). The phase of ongoing EEG oscillations predicts visual perception. *Journal of Neuroscience*, *29*(24), 7869–7876. https://doi.org/10.1523/JNEUROSCI.0113-09.2009

Capotosto, P., Baldassarre, A., Sestieri, C., Spadone, S., Romani, G. L., & Corbetta, M. (2016). Task and regions specific top-down modulation of alpha rhythms in parietal cortex. *Cerebral Cortex*, *27*(10), 4815–4822. https://doi.org/10.1093/cercor/bhw278

Chaumon, M., & Busch, N. A. (2014). Prestimulus neural oscillations inhibit visual perception via modulation of response gain. *Journal of Cognitive Neuroscience*, *26*(11), 2514–2529. https://doi.org/10.1162/jocn_a_00653

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *European Journal of Neuroscience*, *48*(7), 2498–2508. https://doi.org/10.1111/ejn.13747

Cooper, P. S., Darriba, Á., Karayanidis, F., & Barceló, F. (2016). Contextually sensitive power changes across multiple frequency bands underpin cognitive control. *NeuroImage*, *132*, 499–511. https://doi.org/10.1016/j.neuroimage.2016.03.010

Corriveau, I., Fortier-Gauthier, U., Pomerleau, V. J., McDonald, J., Dell'acqua, R., & Jolicoeur, P. (2012). Electrophysiological evidence of multitasking impairment of attentional deployment reflects target-specific processing, not distractor inhibition. *International Journal of Psychophysiology*, *86*(2), 152–159. https://doi.org/10.1016/j.ijpsycho.2012.06.005

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, *99*(3), 225–234. https://doi.org/10.1016/0013-4694(96)95711-9

Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, *25*(2), 514–538. https://doi.org/10.3758/s13423-017-1380-y

Feldmann-Wüstefeld, T., Brandhofer, R., & Schubö, A. (2016). Rewarded visual items capture attention only in heterogeneous contexts. *Psychophysiology*, *53*(7), 1063–1073. https://doi.org/10.1111/psyp.12641

Feldmann-Wüstefeld, T., & Schubö, A. (2016). Intertrial priming due to distractor repetition is eliminated in homogeneous contexts. *Attention, Perception, & Psychophysics*, *78*(7), 1935–1947. https://doi.org/10.3758/s13414-016-1115-6

Feldmann-Wüstefeld, T., Uengoer, M., & Schubö, A. (2015). You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention. *Psychophysiology*, *52*(11), 1483–1497. https://doi.org/10.1111/psyp.12514

Ferrante, O., Patacca, A., Di Caro, V., Della Libera, C., Santandrea, E., & Chelazzi, L. (2018). Altering spatial priority maps via statistical learning of target selection and distractor filtering. *Cortex*, *102*, 67–95. https://doi.org/10.1016/j.cortex.2017.09.027

Foxe, J. J., Murphy, J. W., & De Sanctis, P. (2014). Throwing out the rules: Anticipatory alpha-band oscillatory attention mechanisms during task-set reconfigurations. *European Journal of Neuroscience*, *39*(11), 1960–1972. https://doi.org/10.1111/ejn.12577

Gaspar, J. M., & McDonald, J. J. (2014). Suppression of salient objects prevents distraction in visual search. *The Journal of Neuroscience*, *34*(16), 5658–5666. https://doi.org/10.1523/JNEUROSCI.4161-13.2014

Gladwin, T. E., & de Jong, R. (2005). Bursts of occipital theta and alpha amplitude preceding alternation and repetition trials in a task-switching experiment. *Biological Psychology*, *68*(3), 309–329. https://doi.org/10.1016/j.biopsycho.2004.06.004

Gundlach, C., Moratti, S., Forschack, N., & Müller, M. M. (2020). Spatial attentional selection modulates early visual stimulus processing independently of visual alpha modulations. *Cerebral Cortex*, *30*(6), 3686–3703. https://doi.org/10.1093/cercor/bhz335

Hanslmayr, S., Aslan, A., Staudigl, T., Klimesch, W., Herrmann, C. S., & Bäuml, K. H. (2007). Prestimulus oscillations predict visual perception performance between and within subjects. *NeuroImage*, *37*(4), 1465–1473. https://doi.org/10.1016/j.neuroimage.2007.07.011

Hanslmayr, S., Gross, J., Klimesch, W., & Shapiro, K. L. (2011). The role of alpha oscillations in temporal attention. *Brain Research Reviews*, *67*(1–2), 331–343. https://doi.org/10.1016/j.brainresrev.2011.04.002

Hickey, C., Chelazzi, L., & Theeuwes, J. (2010). Reward changes salience in human vision via the anterior cingulate. *Journal of Neuroscience*, *30*(33), 11096–11103. https://doi.org/10.1523/JNEUROSCI.1026-10.2010

Hickey, C., Di Lollo, V., & McDonald, J. J. (2009). Electrophysiological indices of target and distractor processing in visual search. *Journal of Cognitive Neuroscience*, *21*(4), 760–775. https://doi.org/10.1162/jocn.2009.21039

Kadel, H., Feldmann-Wüstefeld, T., & Schubö, A. (2017). Selection history alters attentional filter settings persistently and beyond top-down control. *Psychophysiology*, *54*(5), 736–754. https://doi.org/10.1111/psyp.12830

Karayanidis, F., Jamadar, S., Ruge, H., Phillips, N., Heathcote, A., & Forstmann, B. U. (2010). Advance preparation in task-switching: Converging evidence from behavioral, brain activation, and model-based approaches. *Frontiers in Psychology*, *1*, 25. https://doi.org/10.3389/fpsyg.2010.00025

Kiesel, A., Miller, J., Jolicoeur, P., & Brisson, B. (2008). Measurement of ERP latency differences: A comparison of single-participant and jackknife-based scoring methods. *Psychophysiology*, *45*(2), 250–274. https://doi.org/10.1111/j.1469-8986.2007.00618.x

Kiss, M., Grubert, A., & Eimer, M. (2013). Top-down task sets for combined features: Behavioral and electrophysiological evidence for two stages in attentional object selection. *Attention, Perception, & Psychophysics*, *75*(2), 216–228. https://doi.org/10.3758/s13414-012-0391-z

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Le Pelley, M. E., Beesley, T., & Griffiths, O. (2011). Overt attention and predictiveness in human contingency learning. *Journal of Experimental Psychology: Animal Behavior Processes*, *37*(2), 220–229. https://doi.org/10.1037/a0021384

Liu, Q., Lin, S., Zhao, G., & Roberson, D. (2016). The effect of modulating top-down attention deployment on the N2pc/PCN. *Biological Psychology*, *117*, 187–193. https://doi.org/10.1016/j.biopsycho.2016.04.004

Longman, C. S., Lavric, A., & Monsell, S. (2013). More attention to attention? An eye-tracking investigation of selection of perceptual attributes during a task switch. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*(4), 1142–1151. https://doi.org/10.1037/a0030409

Luck, S. J., & Hillyard, S. A. (1994a). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology*, *31*(3), 291–308. https://doi.org/10.1111/j.1469-8986.1994.tb02218.x

Luck, S. J., & Hillyard, S. A. (1994b). Spatial filtering during visual search: Evidence from human electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(5), 1000–1014. https://doi.org/10.1037//0096-1523.20.5.1000

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data. *Journal of Neuroscience Methods*, *164*(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Mathewson, K. E., Beck, D. M., Ro, T., Maclin, E. L., Low, K. A., Fabiani, M., & Gratton, G. (2014). Dynamics of alpha control: Preparatory suppression of posterior alpha oscillations by frontal modulators revealed with combined EEG and event-related optical signal. *Journal of Cognitive Neuroscience*, *26*(10), 2400–2415. https://doi.org/10.1162/jocn_a_00637

Mathewson, K. E., Prudhomme, C., Fabiani, M., Beck, D. M., Lleras, A., & Gratton, G. (2012). Making waves in the stream of consciousness: Entraining oscillations in EEG alpha and fluctuations in visual awareness with rhythmic visual stimulation. *Journal of Cognitive Neuroscience*, *24*(12), 2321–2333. https://doi.org/10.1162/jocn_a_00288

Maunsell, J. H., & Treue, S. (2006). Feature-based attention in visual cortex. *Trends in Neurosciences*, *29*(6), 317–322. https://doi.org/10.1016/j.tins.2006.04.001

Mayr, U., & Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. *Journal of Experimental Psychology: General*, *129*(1), 4. https://psycnet.apa.org. https://doi.org/10.1037/0096-3445.129.1.4

Meiran, N., Kessler, Y., & Adi-Japha, E. (2008). Control by action representation and input selection (CARIS): A theoretical framework for task switching. *Psychological Research/Psychologische Forschung*, *72*(5), 473–500. https://doi.org/10.1007/s00426-008-0136-8

Miller, J., Patterson, T., & Ulrich, R. (1998). Jackknife-based method for measuring LRP onset latency differences. *Psychophysiology*, *35*(1), 99–115. https://doi.org/10.1111/1469-8986.3510099

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*(3), 134–140. https://doi.org/10.1016/S1364-6613(03)00028-7

Monsell, S., & Mizon, G. A. (2006). Can the task-cuing paradigm measure an endogenous task-set reconfiguration process? *Journal of Experimental Psychology: Human Perception and Performance*, *32*(3), 493–516. https://doi.org/10.1037/0096-1523.32.3.493

Moore, T., & Zirnsak, M. (2017). Neural mechanisms of selective visual attention. *Annual Review of Psychology*, *68*(1), 47–72. https://doi.org/10.1146/annurev-psych-122414-033400

Nessler, D., Friedman, D., & Johnson, R. (2012). A new account of the effect of probability on task switching: ERP evidence following the manipulation of switch probability, cue informativeness and predictability. *Biological Psychology*, *91*(2), 245–262. https://doi.org/10.1016/j.biopsycho.2012.07.005

O'Brien, J. L., & Raymond, J. E. (2012). Learned predictiveness speeds visual processing. *Psychological Science*, *23*(4), 359–363. https://doi.org/10.1177/0956797611429800

Olivers, C. N., Peters, J., Houtkamp, R., & Roelfsema, P. R. (2011). Different states in visual working memory: When it guides attention and when it does not. *Trends in Cognitive Sciences*, *15*(7), 327–334. https://doi.org/10.1016/j.tics.2011.05.004

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, *2011*, e156869. https://doi.org/10.1155/2011/156869.

Poljac, E., & Yeung, N. (2014). Dissociable neural correlates of intention and action preparation in voluntary task switching. *Cerebral Cortex*, *24*(2), 465–478. https://doi.org/10.1093/cercor/bhs326

Pomerleau, V. J., Fortier-Gauthier, U., Corriveau, I., McDonald, J. J., Dell'Acqua, R., & Jolicœur, P. (2014). The attentional blink freezes spatial attention allocation to targets, not distractors: Evidence from human electrophysiology. *Brain Research*, *1559*, 33–45. https://doi.org/10.1016/j.brainres.2014.02.029

Proskovec, A. L., Wiesman, A. I., & Wilson, T. W. (2019). The strength of alpha and gamma oscillations predicts behavioral switch costs. *NeuroImage*, *188*, 274–281. https://doi.org/10.1016/j.neuroimage.2018.12.016

Reeder, R. R., Olivers, C. N., & Pollmann, S. (2017). Cortical evidence for negative search templates. *Visual Cognition*, *25*(1–3), 278–290. https://doi.org/10.1080/13506285.2017.1339755

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, Perception & Psychophysics*, *72*(6), 1455–1470. https://doi.org/10.3758/APP.72.6.1455

Sawaki, R., & Luck, S. J. (2013). Active suppression after involuntary capture of attention. *Psychonomic Bulletin & Review*, *20*(2), 296–301. https://doi.org/10.3758/s13423-012-0353-4

Sawaki, R., Luck, S. J., & Raymond, J. E. (2015). How attention changes in response to incentives. *Journal of Cognitive Neuroscience*, *27*(11), 2229–2239. https://doi.org/10.1162/jocn_a_00847

Schneider, D., Herbst, S. K., Klatt, L. I., & Wöstmann, M. (2021). Target enhancement or distractor suppression? Functionally distinct alpha oscillations form the basis of attention. *The European Journal of Neuroscience*, 1–10. https://doi.org/10.1111/ejn.15309

Smulders, F. T. (2010). Simplifying jackknifing of ERPs and getting more out of it: Retrieving estimates of participants' latencies. *Psychophysiology*, *47*(2), 387–392. https://doi.org/10.1111/j.1469-8986.2009.00934.x

Theeuwes, J. (1991). Cross-dimensional perceptual selectivity. *Perception & Psychophysics*, *50*(2), 184–193. https://doi.org/10.3758/bf03212219

van Dijk, H., Schoffelen, J. M., Oostenveld, R., & Jensen, O. (2008). Prestimulus oscillatory activity in the alpha band predicts visual discrimination ability. *Journal of Neuroscience*, *28*(8), 1816–1823. https://doi.org/10.1523/JNEUROSCI.1853-07.2008

van Moorselaar, D., & Slagter, H. A. (2020). Inhibition in selective attention. *Annals of the New York Academy of Sciences*, *1464*(1), 204–221. https://doi.org/10.1111/nyas.14304

van Zoest, W., Huber-Huber, C., Weaver, M. D., & Hickey, C. (2021). Strategic distractor suppression improves selective control in human vision. *The Journal of Neuroscience*, *41*(33), 7120–7135. https://doi.org/10.1523/JNEUROSCI.0553-21.2021

Vatterott, D., & Vecera, S. (2012). Experience-dependent attentional tuning of distractor rejection. *Psychonomic Bulletin & Review*, *19*(5), 871–878. https://doi.org/10.3758/s13423-012-0280-4

Weaver, M. D., van Zoest, W., & Hickey, C. (2017). A temporal dependency account of attentional inhibition in oculomotor control. *NeuroImage*, *147*, 880–894. https://doi.org/10.1016/j.neuroimage.2016.11.004

Wykowska, A., & Schubö, A. (2011). Irrelevant singletons in visual search do not capture attention but can produce nonspatial filtering costs. *Journal of Cognitive Neuroscience*, *23*(3), 645–660. https://doi.org/10.1162/jocn.2009.21390

Zhigalov, A., & Jensen, O. (2020). Alpha oscillations do not implement gain control in early visual cortex but rather gating in parieto-occipital regions. *Human Brain Mapping*, *41*(18), 5176–5186. https://doi.org/10.1002/hbm.25183

How to cite this article: Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology*, 59, e13987. https://doi.org/10.1111/psyp.13987

Study II

Abbasi, H., Henare, D., Kadel, H., & Schubö, A. (2023). Selection history and task predictability determine the precision expectations in attentional control. *Psychophysiology*, *e14151*. https://doi.org/10.1111/psyp.14151

Check for updates

Received: 23 November 2021 | Revised: 21 June 2022 | Accepted: 24 June 2022

DOI: 10.1111/psyp.14151

PSYCHOPHYSIOLOGY SPR WILEY

ORIGINAL ARTICLE

Selection history and task predictability determine the precision expectations in attentional control

Hossein Abbasi | **Dion Henare** | **Hanna Kadel** | **Anna Schubö**

Cognitive Neuroscience of Perception and Action, Philipps-University of Marburg, Marburg, Germany

Correspondence
Dion Henare, Philipps-University Marburg, Experimental and Biological Psychology, Gutenbergstraße 18, Marburg 35037, Germany.
Email: dionhenare@gmail.com

Funding information
Deutsche Forschungsgemeinschaft, Grant/Award Number: SFB/TRR 135, project number 222641018 and TP B3

Abstract

Predictive processing frameworks have demonstrated the central role that prediction plays in a range of cognitive processes including bottom-up and top-down mechanisms of attention control. However, relatively little is understood about how predictive processes interact with the third main determinant of attentional priority – selection history. In this experiment, participants developed a history of either color or shape selection while we observed the impact of these histories in an additional singleton search task using behavioral measures and ERP measures of attentional control. Throughout the experiment, participants were encouraged to predict the upcoming display, but prediction errors were either high or low depending on session. Persistent group differences in our results showed that selection history contributes to the precision weighting of a stimulus, and that this is mediated by overall prediction error. Color-singleton distractors captured attention and required greater suppression when participants had a history of color selection; however, these participants gained large benefits when the upcoming stimuli were highly predictable. We suggest that selection history modulates the precision expectations for a feature in a persistent and implicit way, producing an attentional bias that predictability can help to counteract, but cannot prevent or eliminate entirely.

1 | INTRODUCTION

In everyday situations, successful navigation of the world relies on making accurate predictions about where and when important information will be found. Recent work has shown that prediction is not only an important function of the brain, but also a central mechanism that the brain uses to develop effective information processing (den Ouden et al., 2012; Friston, 2009). Predictive coding frameworks of the brain argue that, given the brain's reliance on information produced by the senses, successful interaction with the outside world relies on building and testing predictive models. As such, prediction has been shown to play an important role in a range of cognitive processes including auditory (Bendixen et al., 2012), motor (Ridderinkhof & Brass, 2015; Urgen & Saygin, 2020), and affective systems (Ransom et al., 2020).

To some degree, predictive processing fits into traditional frameworks of visual attention that emphasize a combination of bottom-up and top-down processes (Feldman

---

Hossein Abbasi and Dion Henare shared first authorship.

& Friston, 2010). According to predictive processing, the brain prioritizes stimuli based on two main factors – precision expectations and prediction error. Prediction error is the difference between what the brain predicts will occur and what actually occurs, and should therefore be large for unexpected stimuli. Indeed, research has shown that while neural responses to predicted stimuli are often attenuated, unexpected stimuli generate large responses in accordance with their associated prediction error and capture attention in a bottom-up fashion (Alink et al., 2010; den Ouden et al., 2010; Folk & Remington, 2015; Richter & de Lange, 2019; Todorovic et al., 2011). These prediction errors are also weighted by the second factor, precision expectations (Feldman & Friston, 2010; Kok et al., 2012). Precision refers to the expected reliability of a signal and is essential for ensuring that the brain prioritizes not just any unexpected information, but specifically information that can reliably inform the refinement of predictive models. Recent work has shown that top-down attention is used to increase the expected precision or reliability of a stimulus in an upcoming location, allowing the precision-weighted prediction error of a relevant target to outcompete unexpected stimuli (Gordon et al., 2019; Kok et al., 2012; Smout et al., 2019). In this view, bottom-up and top-down attentional control mechanisms can be understood as processes that modulate the precision-weighted prediction errors that ultimately determine stimulus priority in the brain.

In addition to the classical dichotomy of bottom-up and top-down processing, recent work in the attention literature has highlighted the role of a third major factor, namely, selection history. Selection history refers to the way that an individual's history of interactions with a stimulus can impact on its later selection priority. Feldmann-Wüstefeld et al. (2015) demonstrated this effect using a paradigm in which participants perform two interleaved tasks. In the search task, all participants are required to respond to a line within the target shape singleton, while ignoring a salient color singleton. In the categorization task, however, participants learn to categorize either shape singletons or color singletons depending on their group assignment. The results show that for color group participants, their performance on the search task is especially impaired by the presence of a color distractor. Their results demonstrate the impact that an observer's selection history can have on search, even when it is not relevant (but actually detrimental) to current task performance.

An understanding of how selection history integrates with predictive coding is currently lacking, and may be especially important given selection history's central role in the processing of irrelevant information. The ability to suppress and ignore distractors is presumably a crucial component of successful attentional control, and recently it has been shown that successful suppression of distractors may be achieved primarily through selection history mechanisms (Luck et al., 2021; see also Geng et al., 2019; Chelazzi et al., 2019). Wang et al. (2019) for example have shown that when participants learn to expect a salient distractor to appear in a particular location, the response to that distractor is suppressed. Similarly, van Moorselaar and Slagter (2019, 2020) showed that participants can also use expectations about an upcoming distractor's features to improve their performance. These results are consistent with predictive coding accounts in which predicted stimuli should elicit smaller prediction errors, reducing their processing priority. However, as mentioned above, the final priority of a stimulus is determined by both the prediction error a stimulus evokes, and its expected precision. At this stage we understand relatively little about how selection history interacts with the weighting of precision expectations in order to influence stimulus priority.

The goal of the present study is to examine how selection history impacts on the precision expectations of target dimensions, and how this combines with prediction error to affect distractor capture. To this end, we adapted the task of Feldmann-Wüstefeld et al. (2015) where two groups of participants perform interleaved categorization and search trials. Participants performed these tasks in two different sessions where trial sequence predictability was either high or low. When trial order is highly predictable, prediction errors should be small for all participants, whereas when trial order is only partially predictable, prediction errors will be relatively large. Within each session, the two groups differed with respect to the expected precision of the target dimension. For the shape group, the target in an upcoming display was always a shape singleton, therefore, top-down control and selection history could combine to tune precision expectations for targets across all trials in both sessions. For the color group, selection history could not contribute to the tuning of precision-weighted expectations as the target category changed across trials. Group differences under low predictability therefore represent the color group's inability to tune precision-weighted expectations due to impaired top-down control and selection history. In the high predictable session, the color group gained the use of top-down control to tune expectations from trial to trial, therefore, any group differences that persist in this condition reflect the unique contribution of selection history to precision-weighted expectations in the shape group.

Importantly, we also use EEG to record neural activity during our task, and incorporate a stimulus lateralization technique that provides us with dissociable measures of the neural response to targets and distractors (Feldmann-Wüstefeld et al., 2015; Hickey et al., 2009). The first of these components is the N2pc, an increased negativity that occurs ~200 ms after stimulus onset at parieto-occipital electrodes contralateral to an attended target (Woodman & Luck, 2003) or a salient non-target stimulus (Berggren & Eimer, 2019; Liesefeld et al., 2017). A second prominent lateralized ERP component is the P_D (distractor positivity), a larger positive deflection at contralateral compared to ipsilateral parieto-occipital electrodes, typically elicited by distractors. The P_D component indexes suppression of to-be-ignored salient distractor (Heuer & Schubö, 2020; Hickey et al., 2009; Sawaki & Luck, 2010), or termination of attention after perception completion of a target (Sawaki et al., 2012). Both components were used to evaluate the effect of selection history on attention capture: Feldmann-Wüstefeld et al. (2015) showed that for participants with a history of color categorization, color distractors elicit a larger N2pc and a larger P_D indicating greater attentional capture and an increased need for suppression, respectively. If selection history provides a unique contribution to precision-weighted prediction errors then we should expect similar component differences to appear not only in the low-predictable session of our task, but to remain in the high-predictable session.

2 | METHOD

2.1 | Participants

Thirty four healthy students (6 male) from Philipps University Marburg participated in this study, for course credit or monetary payment (8€/hr). All but four participants were right–handed and all had normal or corrected–to–normal vision. Participants were assigned randomly to either the color or the shape group. Two participants in the shape group had to be excluded from analysis due to excessive eye movements in over 35% of the trials. Written consent for participation was obtained prior to the experiments from participants in the color (mean age ± SD: 21.5 ± 2.6 years) and the shape group (mean age ± SD: 23.2 ± 3.5 years).

2.2 | Stimuli and apparatus

Participants completed the experiments while they were sitting in a comfortable chair in a dimly lit, electrically shielded and sound-attenuated room. They responded via a customizable keypad (Ergodex DX1) placed on their lap. Task presentation was controlled by E-Prime 2.0 routines (Psychology Software Tools, Inc.), running on a standard PC with Windows XP operating system, and presented on a 22" LCD-TN monitor (Samsung Syncmaster 2233) placed at a viewing distance of 100 cm. For auditory feedback two stereo speakers were placed behind the monitor, each on one side (Logitech Z120 2.0). In both experimental tasks, display consisted of eight elements of 2.3° visual angle placed in a circular search array on a dark gray background (RGB 60, 60, 60) equidistant to the screen center (distance screen center to stimulus center: 6.3°; horizontal eccentricity: 5.7°).

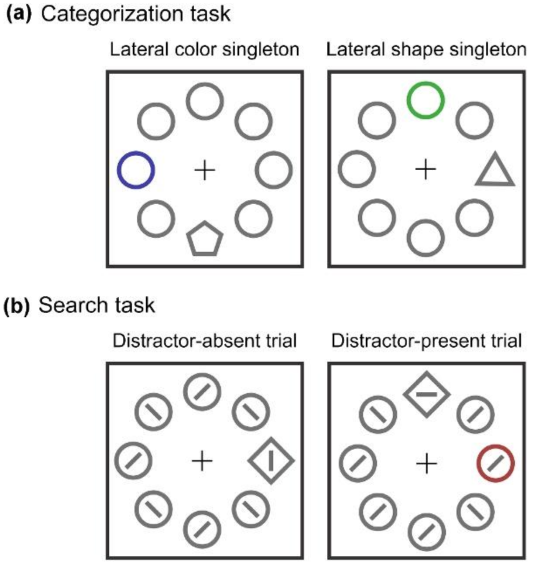


FIGURE 1 (a) Exemplary displays in the categorization task. All categorization trials contained two singletons, one in color and the other in shape. One singleton appeared on the vertical, the other on the horizontal midline. Participants in the color group had to categorize the color singletons by pressing one button for a green and another button for a blue circle. Participants in the shape group had to categorize the shape singletons by pressing one button for a pentagon and another button for a triangle. Participants were naïve to their group assignment when the experiment started and had to learn it on a trial-and-error basis by receiving immediate auditory feedback in incorrect trials. (b) Exemplary displays in the search task. Both groups searched for the diamond-shaped target and reported the orientation (horizontal vs. vertical) of the embedded line. In 50% of the trials, an additional color distractor was presented (right panel) which had to be ignored.

In the *categorization task*, six neutral distractor stimuli (gray circles, RGB 110, 110, 110) and two singletons (see Figure 1a) comprised the display. From the singletons, one had a distinct color, either green (RGB 48, 171, 48) or blue (RGB 48, 48, 171), and the other had a distinct shape, either a triangle or pentagon. All combinations of different singletons (blue–triangle, blue–pentagon, green–triangle, green–pentagon) were presented equally often through the categorization task. Laterality of the stimuli was varied

FIGURE 2 (a) Representation of trial sequences. The letter "C" stands for a categorization trial and the letter "S" stands for a search trial. In high-predictable trial sequences (left panel) the tasks always switched after one repetition. In low-predictable trial sequences (right panel), the pattern was more complex, numbers in the parentheses indicate the likelihood of the respective trial. Each participant completed 25 blocks (with 64 trials per block) for each task sequence in separate sessions. (b) Mean response times in the categorization task for the color (blue) and the shape group (black), separated for high-predictable and low-predictable trial sequences. Error bars represent standard errors of the mean. (c) Mean response times in the search task in high-predictable and low-predictable trial sequence. Blue and back lines represent RTs for the color group and the shape group, respectively. Dashed lines show RTs for trials with an additional colored distractor, solid lines represent RTs for distractor-absent trials. Note that the RT scale in panel C differs from that in panel B. Error bars represent standard errors of the mean. (d) Grande-average difference waves recorded at parieto-occipital electrodes (pool of PO7/8, PO3/4 and P7/8), elicited by lateral singletons in the categorization task in the color (blue lines) and shape group (black lines). Left panels show difference waves observed for high-predictable, right panels for low-predictable task sequences, separately for trials with lateral color singletons (upper panels) and lateral shape singletons (lower panels). Green shadings represent the time window of the N2pc analysis. For illustration purposes, EEG waveforms were low pass filtered at 35 Hz using a zero-phase Butterworth filter of order two.

systematically, to present color and shape singletons at the four positions on the vertical and horizontal midline.

In the *search task*, the target was a diamond shown among seven circles as neutral distractors (see Figure 1b, left). One vertically or horizontally oriented line was embedded in the diamond-shaped singleton while gray neutral distractor stimuli circles (RGB 110, 110, 110) contained a line tilted by ±45°. In 50% of the trials, the additional singleton distractor was presented as a circle with a deviated color to red (RGB 171, 48, 48; distractor–present trials, Figure 1b, right panel). Targets and color distractors appeared at one of the four positions on the vertical and horizontal midline, with the target presented equally often on the vertical and horizontal midline in distractor–absent trials.

2.3 | Procedure

2.3.1 | General trial procedure

Categorization and search trials started with a fixation cross presented for 500 ms, followed by the stimulus display shown for 200 ms, and a blank screen with a central fixation cross, shown for maximal 2000 ms, indicating that participants were supposed to respond. Incorrect responses were followed by a buzzing error sound. After response completion or after the time–out, a 1000 ms inter–trial–interval separated the next trial.

2.3.2 | Feedback–guided learning phase

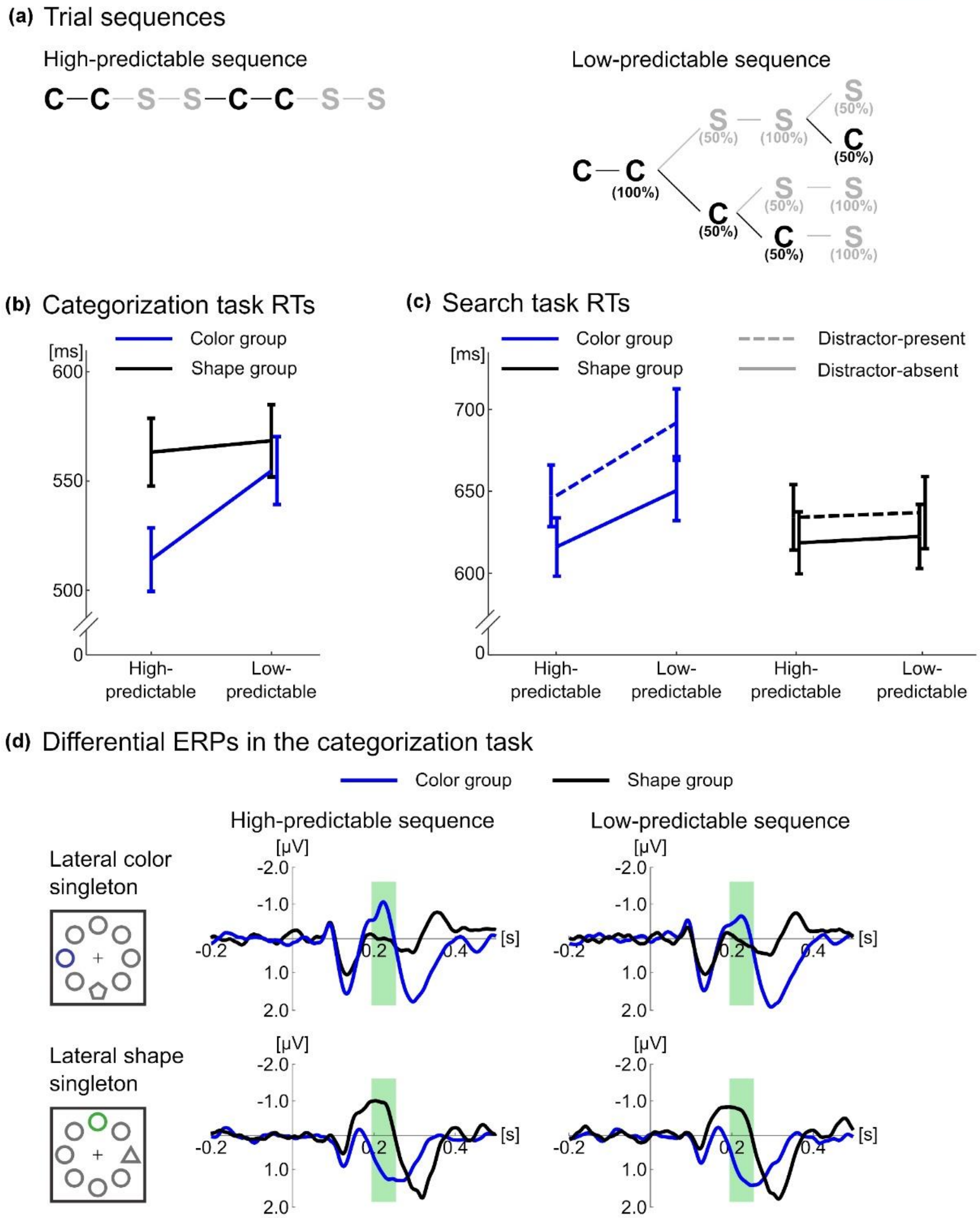
Participants started the learning phase by completing a block of 64 categorization task trials. Before starting the learning phase, they were told that one shape and one color singleton appeared in each trial and they were instructed to respond to each display via the buttons on the left half of the pad with their left hand. They were informed that a buzzing tone indicated an error. They were neither told which stimulus was assigned to which button press, nor that only one dimension was response–relevant, but to find out the correct stimulus–response–mappings with the help of the error feedback. Participants in the color group had to learn to respond to the color singletons (blue or green) and ignore shape singletons, while participants in the shape group had to learn to respond only to shape singletons (triangle or pentagon) and ignore color singletons. In the first 32 trials of the learning phase, stimulus presentation was prolonged to 500 ms for learning facilitation purposes. Participant could proceed to the next block if accuracy was >75%, otherwise they had to repeat the block.

2.3.3 | Mixed practice phase

This block was performed subsequently and combined 32 categorization trials (described above) with 32 search trials in a random order. In the search task, participants from both groups had to report the orientation of the line embedded in the diamond-shaped target (horizontal or vertical) via two response buttons on the right half of the pad with their right hand. Stimulus–response mapping was counterbalanced across participants and groups. In the 32 search task trials of this phase, stimulus presentation was prolonged to 1000 ms for learning facilitation purposes. Participants could proceed to the next block if accuracy was >75%, otherwise they had to repeat the block again.

2.3.4 | Main experiment

After the mixed practice phase, participants had to continue performing both tasks in two different combined experimental sessions performed on separate days. In *high-predictable trial sequences*, trials of the categorization and search task were presented in a sequence of



two trials per task (Figure 2a, left). In a recent study, we have shown that high-predictable trial sequence facilitates proactive task preparation (Abbasi et al., 2022). In *low-predictable trial sequences*, trials were presented in a sequence of variable likelihoods (Figure 2a, right panel). The likelihoods were as follow: While the second trial repeated with a likelihood of 100%, the third repeated or switched with the same likelihood of 50%. The fourth trial depended on the switch/repetition sequence of the first three trials, and was equally likely to be a switch or repeat trial when the first three trials were the same, but always repeated when the last trial had been a switch.

It never happened that more than four consecutive trials from the same task appeared in a row. Because of this pattern of task switching in low-predictable trial sequences, 37% of trials were switch trials and 63% were non-switch trials. Participants were informed about the logic behind high-predictable and low-predictable trial sequences at the beginning of the respective session. In total, participants worked through 25 blocks of 64 trials each on each day, 1600 trials in total and 800 trials in each the categorization and the search task. After each block, performance feedback (response times and accuracy in both tasks) was presented on the screen during a break of at least 10 s. Participants could decide when to continue with the task. Twice throughout the experiment, participants were prompted to take a longer break of several minutes.

2.4 | EEG recording

The EEG was recorded using 64 Ag–AgCl active electrodes (actiCAP by Brain Products GmbH, Munich, Germany), placed according to the International 10–10 layout system. Vertical and horizontal EOGs were measured as differences between electrodes beneath and above the left eye and left and right of the eyes, respectively. Impedance of each electrode was kept below 5 kΩ. All electrodes were referenced to FCz and re–referenced offline to the average of all electrodes. Before referencing, malfunctioning electrodes were identified and interpolated using spherical splines with the spline order of four as implemented in Brain vision analyzer. The signal was recorded with a BrainAmp amplifier (Brain Products, Munich, Germany) at a sampling frequency of 1000 Hz and filtered with a low cutoff filter of 0.016 Hz and a high cutoff filter of 250 Hz (−3 dB cutoff, Butterworth filter, 30 dB/oct roll–off).

2.5 | Data analysis

2.5.1 | Behavioral data

In the categorization task, mean response times (RTs) for trials with correct responses and mean accuracy were computed separately for each task sequence block. Mean RTs and accuracy data were then analyzed using an ANOVA with the between–subject factor categorization task (color vs. shape) and the within–subject factors task predictability (high-predictable vs. low-predictable sequences).

In the search task, mean RTs for trials with correct responses and mean accuracy were computed separately for high-predictable and low-predictable trial sequence sessions and for trials in which a color distractor was absent and present. Mean RTs and accuracy data were then analyzed using an ANOVA with the between–subject factor categorization task (color vs. shape) and the within–subject factors task predictability (high-predictable vs. low-predictable sequences) and distractor presence (distractor–absent vs. distractor–present trials).

First trial in each block, trials with wrong or no responses, and trials with outlier RT (±2 SD from mean RT calculated separately for each participant and separately for each block and task) were removed from all RTs and accuracy analysis. This led to exclusion of 8.94% of trials in the shape and 8.63% in the color group.

2.5.2 | EEG data

Brain Vision Analyzer (Brain Products, Munich, Germany), the Fieldtrip toolbox (Oostenveld et al., 2010) and custom Matlab R2019a (MathWorks, http://www.mathworks.com) scripts were used for off–line EEG data processing.

2.5.3 | Event–related potentials

For the analysis of the target- and distractor-elicited N2pc components and the early and late P_Ds, the EEG was segmented into 700 ms epochs time-locked to display onset, including a 200 ms pre–stimulus baseline. Trials with wrong or without response, and first trials in each block were excluded from further analysis. Vertical EOG (vEOG) was calculated as the difference between electrode below the left eye and Fp1, and the horizontal EOG (hEOG) was calculated as the difference between F9 and F10. The four channels used for EOG calculation were low-pass filtered at 35 Hz. Trials with eyeblinks (vEOG $> \pm 80\,\mu V$) or horizontal eye movements (hEOG $> \pm 50\,\mu V$ amplitude criterion; and hEOG $> \pm 35\,\mu V$ step criterion, within a 40-ms sliding time window) or other channel activities $> \pm 80\,\mu V$ in the first 350 ms after stimulus onset were excluded from analysis. Participants with less than 65% valid trials were excluded from further analysis (two participants from the shape group). The remaining 32 participants had 85.03% artifact–free trials on average. In total, 18.01% of trials had to be excluded in the shape and 11.94% in the color group.

Selection of PO7/8, PO3/4, and P7/8 electrodes for the N2pc and P_D analyses was done based on previous studies (Kadel et al., 2017; Noonan et al., 2016; van Zoest et al., 2021). To determine the time window for the N2pc component, the lateralized ERP from all conditions with a lateralized target were collapsed separately for each task;

the N2pc was identified as the most negative peak in the first 300 ms. A similar approach was taken to determine the time windows for the early P_D (the most positive point within the first 200-ms interval after stimulus onset), the distractor N2pc (the most negative point within the 300-ms interval after stimulus onset), and the late P_D (the most positive point within the 200–350 ms interval after stimulus onset) for all trials with a lateralized distractor in the search task. Next, the time windows were defined as ±30 ms interval around the peak latencies of each ERP component. In the categorization task, the N2pc peaked at 224 ms, the analysis time window was set to 194–254 ms. Mean amplitudes were calculated and forwarded to two separate ANOVAs with the between–subject factor categorization task (color vs. shape) and the within–subject factor task predictability (high-predictable vs. low-predictable). ANOVAs were performed separately for trials with lateral color singleton and lateral shape singleton.

In the search task, the target N2pc peaked at 243 ms, the time window was set to 213–273 ms. The time windows for the distractor N2pc and P_D components were identified from the ERPs averaged across all conditions with a lateralized distractor. The early P_D peaked at 135 ms (time window 105–165 ms), the distractor N2pc peaked at 231 ms (time window 201–261 ms), and the late P_D peaked at 294 ms (time window 264–324 ms). For each component, mean amplitudes were calculated and forwarded to a two–way ANOVA with the between–subject factor categorization task (color vs. shape), and the within–subject factor task predictability (high–predictable vs. low-predictable).

In addition to mean amplitude, the onset latency of the target N2pc and the late P_D was analyzed using a jackknife–based approach (Kiesel et al., 2008; Miller et al., 1998). The onset was determined as the time point at which 50% of the target N2pc (lateral target conditions) or the late P_D (lateral distractor condition) amplitude was reached. Mean onsets were forwarded to a two–way ANOVA with the between–subject factor categorization task (color vs. shape) and the within–subject factor task predictability (high-predictable vs. low-predictable) separately for distractor–absent trials, distractor–present trials with the lateral target and distractor–present trials with the lateral distractor.

3 | RESULTS

3.1 | Categorization task

3.1.1 | Behavioral results (Figure 2b)

On average, participants in both groups responded with similar speed to their respective singleton, (color group: $M \pm SEM$ = 534 ± 13 ms; shape group: M = 566 ± 14 ms), $F(1,30) = 2.56$, $p = .12$. Responses were, however, faster in the high-predictable (M = 539 ± 11 ms) than in the low-predictable trial sequence (M = 562 ± 11 ms), $F(1,30) = 5.38$, $p = .03$, $\eta_p^2 = .15$, indicating more efficient target selection with an increase in predictability. Participants in the color group seemed to benefit more from predictability ($M_{high\text{-}pred.}$ = 514 ± 15 ms vs. $M_{low\text{-}pred.}$ = 555 ± 16 ms; two-sided paired t-test: $t[16] = 3.35$, $p = .004$) than participants in the shape group ($M_{high\text{-}pred.}$ = 563 ± 16 ms vs. $M_{low\text{-}pred.}$ = 568 ± 17 ms; two-sided paired t test: $t[14] = .33$, $p = .75$), yet the two-way interaction failed to reach significance, $F(1,30) = 3.20$, $p = .08$, ${\eta_p}^2 = .10$. Accuracy results did not reveal any main effect or interaction (all $p > .2$).

3.2 | ERP results (Figure 2d)

The analysis was done separately for displays with the color singleton on the lateral and displays with the shape singleton on the lateral.

3.2.1 | Color singleton on the lateral (Figure 2d, upper panels)

Electrophysiological results revealed a larger N2pc in high-predictable ($\Delta M = -0.31 \pm .12\,\mu V$) than in low-predictable trial sequence ($\Delta M = -0.17 \pm .11\,\mu V$), but this difference failed to reach significance, $F(1,30) = 3.81$, $p = .06$, $\eta_p^2 = .11$. There was an N2pc for participants in the color group ($\Delta M = -0.52 \pm .15\,\mu V$), indicating that they attended to the color singleton, but not for participants in the shape group ($\Delta M = 0.04 \pm .16\,\mu V$), $F(1,30) = 6.67$, $p = .01$, $\eta_p^2 = .18$. The interaction between the factors was not significant ($p > .2$).

3.2.2 | Shape singleton on the lateral (Figure 2d, lower panels)

Electrophysiological results showed an N2pc for participants in the shape group ($\Delta M = -0.67 \pm .18\,\mu V$), revealing that they attended to the shape singleton, and a positivity for participants in the color group ($\Delta M = 1.02 \pm .17\,\mu V$), $F(1,30) = 48.09$, $p < .001$, $\eta_p^2 = .62$. No other effect or interaction emerged (all ps $> .1$).

3.3 | Search task

3.3.1 | Behavioral results (Figure 2c)

As expected, participants responded slower in the distractor–present trials (M = 653 ± 12 ms) than in the distractor–absent trials ($M = 627 \pm 11$ ms), $F(1,30) = 67.35$, $p < .001$, $\eta_p^2 = .69$, indicating attention capture. This distractor cost was more than twice as large for participants in the color group ($\Delta M = 36 \pm 5$ ms: $M_{dist.pres.} = 670 \pm 17$ ms vs. $M_{dist.abs.} = 633 \pm 15$ ms) when compared to participants in the shape group ($\Delta M = 15 \pm 4$ ms: $M_{dist.pres.} = 636 \pm 18$ ms vs. $M_{dist.abs.} = 620 \pm 16$ ms), $F(1,30) = 11.50$, $p = .002$, $\eta_p^2 = .28$. As indicated by a significant task predictability × distractor-presence × categorization task interaction, distractor cost was reduced in high-predictable trial sequences in participants in the color group ($\Delta M_{high\text{-}pred.} = 31 \pm 5$ ms vs. $\Delta M_{low\text{-}pred.} = 41 \pm 5$ ms, Figure 2c left side), indicating that they benefitted from predictability in handling the distractor, while participants in the shape group showed no difference ($\Delta M_{high\text{-}pred.} = 16 \pm 5$ ms vs. $\Delta M_{low\text{-}pred.} = 15 \pm 4$ ms, Figure 2c right side), $F(1,30) = 5.14$, $p = .03$, $\eta_p^2 = .15$. No other effect or interaction emerged (all $ps > .07$).

Participants were less accurate in the distractor–present trials ($M = 96.3 \pm .2\%$) compared to the distractor–absent trials ($M = 96.8 \pm .2\%$), $F(1,30) = 5.42$, $p = .03$, $\eta_p^2 = .15$. No other effect or interaction emerged (all $ps > .3$).

3.3.2 | ERP results: Distractor–absent trials (Figure 3a)

Electrophysiological results showed a target N2pc, $F(1,30) = 62.04$, $p < .001$, $\eta_p^2 = .67$, that tended to be larger in the high-predictable ($\Delta M = -1.14 \pm 0.14\,\mu V$) than in the low-predictable trial sequence ($\Delta M = -0.90 \pm 0.15\,\mu V$), but this difference was not significant, $F(1,30) = 3.31$, $p = .08$, $\eta_p^2 = .10$. However, there was a large effect of predictability on N2pc amplitude for participants in the color group ($\Delta M_{high\text{-}pred.} = -1.20 \pm 0.19\,\mu V$, $\Delta M_{low\text{-}pred.} = -0.68 \pm 0.21\,\mu V$), but no difference for participants in the shape group ($\Delta M_{high\text{-}pred.} = -1.08 \pm 0.20\,\mu V$, $\Delta M_{low\text{-}pred.} = -1.12 \pm 0.22\,\mu V$), $F(1,30) = 4.58$, $p = .04$, $\eta_p^2 = .13$. No other effect emerged in the amplitude measure (all $ps > .5$). However, the onset of the target N2pc in the color group ($220 \pm .2$ ms) was later than that in the shape group ($209 \pm .2$ ms), $F_c(1,30) = 5.36$, $p = .03$, $\eta_p^2 = .98$.

3.3.3 | Distractor–present trials: Lateral target (Figure 3b)

Analyses showed the presence of a target N2pc ($F(1,30) = 32.34$, $p < .001$, $\eta_p^2 = .52$), but neither an effect of categorization task, nor of task predictability nor the interaction (all $ps > .1$). The onset of the target N2pc was later in the color group ($221 \pm .4$ ms) than in the shape group ($212 \pm .4$ ms); however, this difference was not significant ($p > .2$).

3.4 | Distractor–present trials: Lateral distractor (Figure 3c)

3.4.1 | Early P_D

The ANOVA showed the emergence of an early P_D component, $F(1,30) = 61.10$, $p < .001$, $\eta_p^2 = .67$. Crucially, increasing task predictability led to an increase in early P_D amplitude in the color group ($\Delta M_{high\text{-}pred.} = 0.79 \pm 0.14\,\mu V$, $\Delta M_{low\text{-}pred.} = 0.44 \pm 0.10\,\mu V$), but not in the shape group ($\Delta M_{high\text{-}pred.} = 0.56 \pm 0.15\,\mu V$, $\Delta M_{low\text{-}pred.} = 0.61 \pm 0.11\,\mu V$), $F(1,30) = 4.36$, $p = .045$, $\eta_p^2 = .13$. No other effect or interaction emerged (all $ps > .1$).

3.4.2 | Distractor N2pc

A significant categorization task × task predictability interaction revealed a distractor N2pc, indicative of attention capture, for participants in the color group in low-predictable trial sequence ($\Delta M = -0.32 \pm 0.14\,\mu V$), which was virtually absent in high-predictable trial sequence ($\Delta M = -0.03 \pm 0.16\,\mu V$) and for participants in the shape group ($\Delta M_{low\text{-}pred.} = 0.11 \pm 0.15\,\mu V$ vs. $\Delta M_{high\text{-}pred.} = -0.14 \pm 0.17\,\mu V$), $F(1,30) = 8.32$, $p = .007$, $\eta_p^2 = .22$. No other effect or interaction emerged (all $ps > .4$).

3.4.3 | Late P_D

The late P_D, indicative of suppression, was more pronounced in the low-predictable ($\Delta M = 1.03 \pm 0.14\,\mu V$) than in the high-predictable trial sequence ($\Delta M = 0.56 \pm 0.15\,\mu V$), $F(1,30) = 11.99$, $p = .002$, $\eta_p^2 = .29$. The late P_D was also more pronounced in the color group ($\Delta M = 1.39 \pm 0.18\,\mu V$) than in the shape group ($\Delta M = 0.19 \pm 0.19\,\mu V$), $F(1,30) = 21.81$, $p < .001$, $\eta_p^2 = .42$. Notably, unlike the early P_D, the late P_D showed no interaction between group and task predictability ($p = .17$). The onset latency analysis did not reveal any difference between the onset of the late P_D between the shape group ($273 \pm .3$ ms) and the color group ($264 \pm .3$ ms), $p > .2$.

4 | DISCUSSION

The results replicated the robust effect of selection history on stimulus priority that has been shown previously (Feldmann-Wüstefeld et al., 2015; Henare et al., 2020; Kadel et al., 2017). For participants who attended to color in the categorization task, color singleton distractors required greater suppression and produced larger distractor costs in the search task. Notably, these selection history

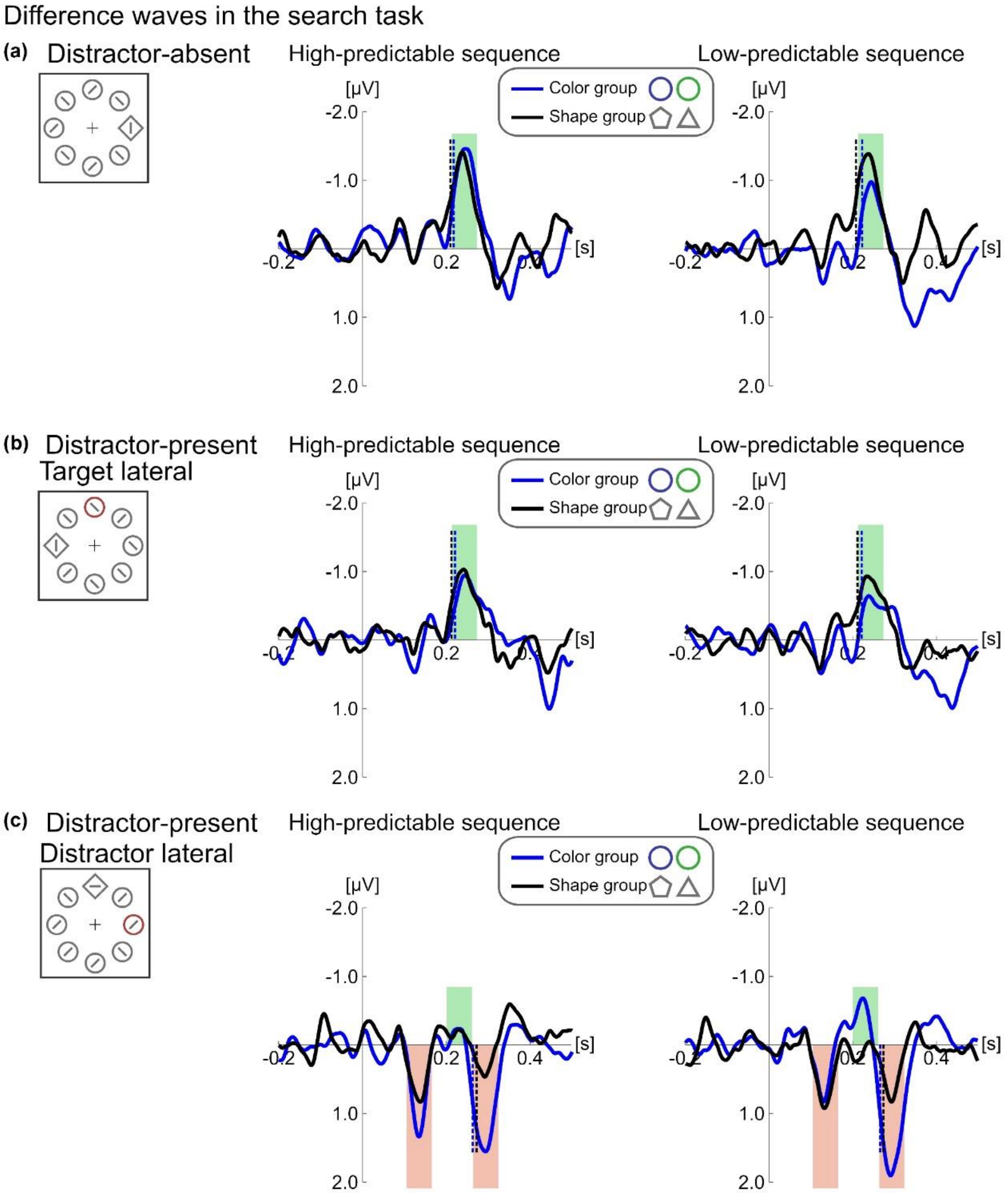


FIGURE 3 ERP difference waves computed from contralateral minus ipsilateral waveforms recorded at parieto-occipital electrodes (pool of PO7/8, PO3/4 and P7/8) in the search task, (a) in distractor-absent trials, (b) in trials with a distractor presented on the vertical midline of the visual field, and (c) in trials with a distractor presented on the horizontal midline of the visual field. ERPs are visualized separately for high-predictable (left panels) and low-predictable trial sequence blocks (right panels). Blue lines represent difference waves of the color group, black lines represent difference waves of the shape group. Green shadings represent the time window of the N2pc analyses, red shadings represent the time window used in the P_D analyses. For illustration purposes, EEG waveforms were low pass filtered at 35 Hz using a zero-phase Butterworth filter of order two.

effects interacted with the trial order predictability within each session. For participants in the color group, high predictability produced an enhanced N2pc to search targets and faster response times, whereas the shape group received no such benefit. High predictability also eliminated the distractor N2pc for participants in the color group, where instead we observed an enhanced early P_D preceding capture, and reduced distractor costs. Again, these effects were absent in the shape group, who showed no distractor N2pc irrespective of predictability, and their early P_D amplitude and distractor costs were unchanged. The late P_D was also significantly reduced by high predictability, this time equivalently for both groups.

The results of the color group demonstrate the role that predictability can play in preventing capture by anticipated color singletons. In the low predictability condition, the color group could not reliably predict whether the upcoming target would be a shape or color singleton. As a consequence, ERP results replicated previous findings that color singletons in the search task captured attention, and required substantial late suppression (Feldmann-Wüstefeld et al., 2015; Henare et al., 2020; Kadel et al., 2017). At the same time, selection of search targets was impaired and response time distractor costs were large. However, in the high predictability condition where participants knew how to expect a diamond target and red singleton distractor, the distractor elicits a large early P_D that precedes capture. Subsequently, the distractor N2pc was eliminated, late suppression was reduced, and target selection was enhanced. These results imply that increased predictability gave participants the ability to use top-down control to tune their precision expectations for the upcoming stimuli, preventing capture by the salient distractor and improving task performance.

The findings in the color group extend on recent work in which participants performed a similar task that used interleaved blocks of either perfectly predictable, or completely random task order (Abbasi et al., 2022). In their results, Abbasi and colleagues also observed an early P_D in the color group; however, its amplitude was unaffected by whether trial order was predictable, or random. The fact that we observed significant early P_D modulation in our results as predictability increased, is likely due to the way that participants were incentivized to use prediction and preparation. Whereas Abbasi and colleagues had participants frequently performing blocks of completely random trials, in our task trial order was never completely unpredictable. This ensures that participants are always encouraged to invest cognitive resources in making predictions about an upcoming trial, and evaluating the outcome of those predictions at the end of the trial. As a result, a greater reliance on the use of predictive processes and less emphasis on reactive control mechanisms (see Braver, 2012, for discussion of reactive and proactive control mechanisms), produces a larger effect of predictability on early stimulus processing. Additionally, the predictability conditions in our task remain consistent for an entire session rather than changing from block to block, once again allowing for greater reliance on predictive processes. By encouraging a longer-term development and refinement of predictive models throughout our task, we can observe the effects of predictive processing on proactive control in the color group.

Notably, predictability had a less pervasive effect on stimulus processing in the shape group. In both the high and low predictability condition, the shape group were always able to reliably predict the dimension of their upcoming target and distractor and tune their precision expectations accordingly. As a result, we see that even in the low predictability condition there is no distractor N2pc elicited by the color singleton, and therefore dimension level information about the distractor seems sufficient for preventing attention capture. In the high-predictable condition, the shape group gained additional knowledge of the specific, within-dimension features of the target and distractor in search trials. This ability to predict with certainty the specific feature of an upcoming distractor reduced prediction errors and resulted in a reduction of the late P_D component, an effect that has been linked to improved reactive suppression of a salient distractor (Heuer & Schubö, 2020).

The fact that predictability did not appear to impact on early processing for the shape group is not unexpected in the context of recent work detailing the effect of dimensionality on distractor interference. Liesefeld and Müller (2019) have shown that different-dimension distractors produce significantly weaker interference on search tasks than same-dimension distractors. Similarly, while participants can learn to anticipatorily suppress distractors of a given dimension at a particular location, there is no within-dimension specificity to this effect – all distractors within a dimension are suppressed equally at that location (Failing et al., 2019). This could imply that the interference caused by different-dimension distractors in the shape group is already relatively small, limiting any possible benefits from feature-specific predictions. Additionally, while the shape group may have the opportunity to take advantage of greater proactive suppression in the high predictability condition, recent work has shown that participants may not choose to use this intensive form of suppression unless strongly incentivized by factors like increased task difficulty (Conci et al., 2019), a lack of target predictability (van Moorselaar et al., 2020), or enforced task set instantiation through voluntary choice paradigms (Henare & Schubö, 2021).

One potential open question is the interpretation of an early P_D that is occurring around 100 ms post-stimulus.

While initial reports of an early P_D attributed this activity to lower level mechanisms such as stimulus display imbalances and salience (Jannati et al., 2013; Luck & Hillyard, 1994), more recently it has been interpreted as including more cognitive aspects such as the processes of suppression that are observed in the later P_D activity (Abbasi et al., 2022; Gokce et al., 2014; van Zoest et al., 2021; Weaver et al., 2017). Recently, van Moorselaar et al. (2021) made the distinction that early P_D might reflect a more short-term bias resulting from intertrial priming, while the later P_D component reflects a more conventional view of suppression based on long term learning. In their task, participants performed an additional singleton search where the salient distractor was likely to appear in a specific location across time. Participants who showed no evidence of learning this distractor-location association produced only an early P_D, whereas those participants who learned to use the location probability produced the conventional late P_D. On the basis of this pattern of results, van Moorselaar and Slagter suggested that the non-learners benefitted only from the fact that for any given trial, the distractor location was likely to repeat from the previous trial, and therefore the early P_D reflects this intertrial priming.

The description of early P_D as an index of intertrial repetition is unlikely to account for our finding that early P_D increases for color group participants in the high predictability condition. The distractor location is randomized in our task and therefore intertrial location repetition is equivalent in all conditions, leaving open only the possibility that early P_D is similarly modulated by feature-based intertrial repetition. However, if distractor feature repetition increased early P_D amplitude then we would expect a larger early P_D in the low-predictability condition which had more task repetitions than the high-predictable condition. Our results show the opposite effects, with a larger early P_D for participants in the high-predictability condition, and only for the color group. Our use of balanced stimulus displays that are identical in all conditions also rules out accounts based on lower level physical features. The early P_D in our data therefore is best explained by the view that it reflects an early suppression mechanism that precedes distractor capture.

It is possible, therefore, that the large early P_D observed in the color group is indicative of proactive suppression. Participants in that group are using predictability to proactively adjust their precision expectations for the distractor feature, resulting in early suppression of its representation and preventing attentional capture. This is consistent with Wang et al. (2019) who used evidence of an early P_D and lack of N2pc to suggest that participants can proactively suppress the location of a likely distractor. Notably in our task, participants in the shape group did not show this evidence of proactive distractor suppression, their early P_D was unaffected by predictability and their behavioral performance remained high. Instead, the shape group showed only a reduction in the late P_D, which has been shown previously to occur when a distractor stimulus requires less reactive suppression (Heuer & Schubö, 2020). This may reflect the fact that for all participants in this condition, prediction error has decreased as all participants can anticipate which stimuli they are about to encounter. For shape group participants, this is sufficient to perform optimally as prediction error is low and shape singletons are assigned high precision by both top-down mechanisms and selection history. For color group participants prediction error is similarly low, however, their selection history continues to conflict with the upcoming task and, therefore, they must proactively prepare to counteract the high precision-weighting of color singletons that has developed from their selection history. The group differences in this condition, therefore, imply that selection history increases the precision expectations of a feature (e.g., color singletons in the color group), persistently increasing the salience of that feature, even when it can be anticipated as a distractor in the upcoming trial. The color group cannot use their predictions to prevent the elicitation of that increased saliency signal, but can prepare to counteract it when it arrives in order to prevent its impact on performance.

In summary, our results imply that while top-down mechanisms can be used to tune precision expectations and handle salient distractors, this approach is effortful and, therefore, only employed when precision expectations have not already been tuned appropriately by selection history (as, in our case, in the color group). The benefits that this group receives when the upcoming feature is predictable, reflect the benefits that participants received in other tasks, when the location of a likely distractor was predictable (Wang et al., 2019). The color group uses predictability to proactively prepare for, and counteract, the anticipated distraction caused by the precision expectations that their selection history imposes. Conversely, the shape group gains relatively little behavioral benefit from the task session where predictions are 100% reliable. The shape group's performance is high in both conditions, and their distractor processing shows that predictability decreases only the amount of late suppression that they need to perform. While precision expectations have so far been considered a mechanism of top-down control, these results show that selection history also modulates precision expectations of a feature in an implicit, persistent way that can modulate the saliency of a stimulus. If selection history and top-down control are both operating by modulating precision expectations, then this may explain why research has consistently shown how limited the use of top-down control can be in the face of selection history biases (Abbasi et al., 2022; Henare et al., 2020; Kadel et al., 2017).

5 | CONCLUSION

Our results show the role that selection history plays in the operation of predictive coding models in attentional control. Extended experience selecting and responding to a particular feature dimension appeared to increase the precision expectations of that feature dimension. For the color group, this meant that color singletons produce higher precision-weighted prediction errors and are more likely to capture attention as indexed by a distractor N2pc, a large late P_D, and larger distractor costs. When these participants can reliably predict that color will be a distractor, they proactively prepare for the saliency signal this will produce and suppress it before capture can take place. This kind of proactive preparation only takes place when incentivized by the task demands. Participants with a history of shape selection do not use predictability in the same way to enhance early suppression, their lack of color selective history means that such proactive suppression is not needed in order to maintain high performance. Selection history appears to modulate precision expectations for the relevant features persistently and implicitly, enhancing the precision-weighted prediction error of that feature, in spite of the immediate influence that top-down control mechanisms attempt to exert.

AUTHOR CONTRIBUTIONS

Hossein Abbasi: Data curation; formal analysis; methodology; visualization; writing – original draft; writing – review and editing. **Dion Henarei:** investigation; methodology; validation; writing original draft; writing review editing. **Hanna Kadel:** Conceptualization; data curation; investigation; methodology; project administration; writing – review and editing. **Anna Schubö:** Conceptualization; funding acquisition; investigation; methodology; project administration; resources; supervision; writing – review and editing.

FUNDING INFORMATION

This research was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – SFB/TRR 135, project number 222641018, TP B3.

ACKNOWLEDGMENT

Open Access funding enabled and organized by Projekt DEAL.

ORCID

Hossein Abbasi https://orcid.org/0000-0002-9515-4859
Dion Henare https://orcid.org/0000-0003-4788-0677

REFERENCES

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology*, *59*(4), e13987. https://doi.org/10.1111/psyp.13987

Alink, A., Schwiedrzik, C. M., Kohler, A., Singer, W., & Muckli, L. (2010). Stimulus predictability reduces responses in primary visual cortex. *Journal of Neuroscience*, *30*(8), 2960–2966. https://doi.org/10.1523/JNEUROSCI.3730-10.2010

Bendixen, A., SanMiguel, I., & Schröger, E. (2012). Early electrophysiological indicators for predictive processing in audition: A review. *International Journal of Psychophysiology*, *83*(2), 120–131. https://doi.org/10.1016/j.ijpsycho.2011.08.003

Berggren, N., & Eimer, M. (2019). The roles of relevance and expectation for the control of attention in visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(9), 1191–1205. https://doi.org/10.1037/xhp0000666

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Chelazzi, L., Marini, F., Pascucci, D., & Turatto, M. (2019). Getting rid of visual distractors: The why, when, how, and where. *Current Opinion in Psychology*, *29*, 135–147. https://doi.org/10.1016/j.copsyc.2019.02.004

Conci, M., Deichsel, C., Müller, H. J., & Töllner, T. (2019). Feature guidance by negative attentional templates depends on search difficulty. *Visual Cognition*, *27*(3–4), 317–326. https://doi.org/10.1080/13506285.2019.1581316

den Ouden, H., Kok, P., & De Lange, F. (2012). How prediction errors shape perception, attention, and motivation. *Frontiers in Psychology*, *3*, 548. https://doi.org/10.3389/fpsyg.2012.00548

den Ouden, H. E. M., Daunizeau, J., Roiser, J., Friston, K. J., & Stephan, K. E. (2010). Striatal prediction error modulates cortical coupling. *Journal of Neuroscience*, *30*(9), 3210–3219. https://doi.org/10.1523/JNEUROSCI.4458-09.2010

Failing, M., Feldmann-Wüstefeld, T., Wang, B., Olivers, C., & Theeuwes, J. (2019). Statistical regularities induce spatial as well as feature-specific suppression. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(10), 1291–1303. https://doi.org/10.1037/xhp0000660

Feldman, H., & Friston, K. (2010). Attention, uncertainty, and free-energy. *Frontiers in Human Neuroscience*, *4*, 215. https://doi.org/10.3389/fnhum.2010.00215

Feldmann-Wüstefeld, T., Uengoer, M., & Schubö, A. (2015). You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention. *Psychophysiology*, *52*(11), 1483–1497. https://doi.org/10.1111/psyp.12514

Folk, C. L., & Remington, R. W. (2015). Unexpected abrupt onsets can override a top-down set for color. *Journal of Experimental Psychology. Human Perception and Performance*, *41*(4), 1153–1165. https://doi.org/10.1037/xhp0000084

Friston, K. (2009). The free-energy principle: A rough guide to the brain? *Trends in Cognitive Sciences*, *13*(7), 293–301. https://doi.org/10.1016/j.tics.2009.04.005

Geng, J. J., Won, B. Y., & Carlisle, N. B. (2019). Distractor ignoring: Strategies, learning, and passive filtering. *Current Directions in Psychological Science*, *28*(6), 600–606. https://doi.org/10.1177/0963721419867099

Gokce, A., Geyer, T., Finke, K., Müller, H. J., & Töllner, T. (2014). What pops out in positional priming of pop-out: Insights from event-related EEG lateralizations. *Frontiers in Psychology*, *5*, 688. https://doi.org/10.3389/fpsyg.2014.00688

Gordon, N., Tsuchiya, N., Koenig-Robert, R., & Hohwy, J. (2019). Expectation and attention increase the integration of top-down and bottom-up signals in perception through different pathways. *PLoS Biology*, *17*(4), e3000233. https://doi.org/10.1371/journal.pbio.3000233

Henare, D. T., Kadel, H., & Schubö, A. (2020). Voluntary control of task selection does not eliminate the impact of selection history on attention. *Journal of Cognitive Neuroscience*, *32*(11), 2159–2177. https://doi.org/10.1162/jocn_a_01609

Henare, D. T., & Schubö, A. (2021). Voluntary choice tasks increase control settings and reduce capture. *Visual Cognition*, *29*(9), 626–630. https://doi.org/10.1080/13506285.2021.1936726

Heuer, A., & Schubö, A. (2020). Cueing distraction: Electrophysiological evidence for anticipatory active suppression of distractor location. *Psychological Research*, *84*(8), 2111–2121. https://doi.org/10.1007/s00426-019-01211-4

Hickey, C., Di Lollo, V., & McDonald, J. J. (2009). Electrophysiological indices of target and distractor processing in visual search. *Journal of Cognitive Neuroscience*, *21*(4), 760–775. https://doi.org/10.1162/jocn.2009.21039

Jannati, A., Gaspar, J. M., & McDonald, J. J. (2013). Tracking target and distractor processing in fixed-feature visual search: Evidence from human electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(6), 1713–1730. https://doi.org/10.1037/a0032251

Kadel, H., Feldmann-Wüstefeld, T., & Schubö, A. (2017). Selection history alters attentional filter settings persistently and beyond top-down control. *Psychophysiology*, *54*(5), 736–754. https://doi.org/10.1111/psyp.12830

Kiesel, A., Miller, J., Jolicœur, P., & Brisson, B. (2008). Measurement of ERP latency differences: A comparison of single-participant and jackknife-based scoring methods. *Psychophysiology*, *45*(2), 250–274. https://doi.org/10.1111/j.1469-8986.2007.00618.x

Kok, P., Rahnev, D., Jehee, J. F. M., Lau, H. C., & de Lange, F. P. (2012). Attention reverses the effect of prediction in silencing sensory signals. *Cerebral Cortex*, *22*(9), 2197–2206. https://doi.org/10.1093/cercor/bhr310

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage*, *156*, 166–173. https://doi.org/10.1016/j.neuroimage.2017.05.016

Liesefeld, H. R., & Müller, H. J. (2019). Distractor handling via dimension weighting. *Current Opinion in Psychology*, *29*, 160–167. https://doi.org/10.1016/j.copsyc.2019.03.003

Luck, S. J., Gaspelin, N., Folk, C. L., Remington, R. W., & Theeuwes, J. (2021). Progress toward resolving the attentional capture debate. *Visual Cognition*, *29*(1), 1–21. https://doi.org/10.1080/13506285.2020.1848949

Luck, S. J., & Hillyard, S. A. (1994). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology*, *31*(3), 291–308. https://doi.org/10.1111/j.1469-8986.1994.tb02218.x

Miller, J., Patterson, T., & Ulrich, R. (1998). Jackknife-based method for measuring LRP onset latency differences. *Psychophysiology*, *35*(1), 99–115. https://doi.org/10.1111/1469-8986.3510099

Noonan, M. P., Adamian, N., Pike, A., Printzlau, F., Crittenden, B. M., & Stokes, M. G. (2016). Distinct mechanisms for distractor suppression and target facilitation. *The Journal of Neuroscience*, *36*(6), 1797–1807. https://doi.org/10.1523/JNEUROSCI.2133-15.2016

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.M. (2010). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, *2011*, e156869. https://doi.org/10.1155/2011/156869

Ransom, M., Fazelpour, S., Markovic, J., Kryklywy, J., Thompson, E. T., & Todd, R. M. (2020). Affect-biased attention and predictive processing. *Cognition*, *203*, 104370. https://doi.org/10.1016/j.cognition.2020.104370

Richter, D., & de Lange, F. P. (2019). Statistical learning attenuates visual activity only for attended stimuli. *eLife*, *8*, e47869. https://doi.org/10.7554/eLife.47869

Ridderinkhof, K. R., & Brass, M. (2015). How kinesthetic motor imagery works: A predictive-processing theory of visualization in sports and motor expertise. *Journal of Physiology-Paris*, *109*(1), 53–63. https://doi.org/10.1016/j.jphysparis.2015.02.003

Sawaki, R., Geng, J. J., & Luck, S. J. (2012). A common neural mechanism for preventing and terminating the allocation of attention. *Journal of Neuroscience*, *32*(31), 10725–10736. https://doi.org/10.1523/JNEUROSCI.1864-12.2012

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, Perception, & Psychophysics*, *72*(6), 1455–1470. https://doi.org/10.3758/APP.72.6.1455

Smout, C. A., Tang, M. F., Garrido, M. I., & Mattingley, J. B. (2019). Attention promotes the neural encoding of prediction errors. *PLoS Biology*, *17*(2), e2006812. https://doi.org/10.1371/journal.pbio.2006812

Todorovic, A., van Ede, F., Maris, E., & de Lange, F. P. (2011). Prior expectation mediates neural adaptation to repeated sounds in the auditory cortex: An MEG study. *Journal of Neuroscience*, *31*(25), 9118–9123. https://doi.org/10.1523/JNEUROSCI.1425-11.2011

Urgen, B. A., & Saygin, A. P. (2020). Predictive processing account of action perception: Evidence from effective connectivity in the action observation network. *Cortex*, *128*, 132–142. https://doi.org/10.1016/j.cortex.2020.03.014

van Moorselaar, D., Daneshtalab, N., & Slagter, H. A. (2021). Neural mechanisms underlying distractor inhibition on the basis of feature and/or spatial expectations. *Cortex*, *137*, 232–250. https://doi.org/10.1016/j.cortex.2021.01.010.

van Moorselaar, D., Lampers, E., Cordesius, E., & Slagter, H. A. (2020). Neural mechanisms underlying expectation-dependent inhibition of distracting information. *eLife*, *9*, e61048. https://doi.org/10.7554/eLife.61048

van Moorselaar, D., & Slagter, H. A. (2019). Learning what is irrelevant or relevant: Expectations facilitate distractor inhibition and target facilitation through distinct neural mechanisms. *Journal of Neuroscience*, *39*(35), 6953–6967. https://doi.org/10.1523/JNEUROSCI.0593-19.2019

van Moorselaar, D., & Slagter, H. A. (2020). Inhibition in selective attention. *Annals of the New York Academy of Sciences*, *1464*(1), 204–221. https://doi.org/10.1111/nyas.14304

van Zoest, W., Huber-Huber, C., Weaver, M. D., & Hickey, C. (2021). Strategic distractor suppression improves selective control in human vision. *Journal of Neuroscience*, *41*(33), 7120–7135. https://doi.org/10.1523/JNEUROSCI.0553-21.2021

Wang, B., van Driel, J., Ort, E., & Theeuwes, J. (2019). Anticipatory distractor suppression elicited by statistical regularities in visual search. *Journal of Cognitive Neuroscience*, *31*(10), 1535–1548. https://doi.org/10.1162/jocn_a_01433

Weaver, M. D., van Zoest, W., & Hickey, C. (2017). A temporal dependency account of attentional inhibition in oculomotor control. *NeuroImage*, *147*, 880–894. https://doi.org/10.1016/j.neuroimage.2016.11.004

Woodman, G. F., & Luck, S. J. (2003). Serial deployment of attention during visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(1), 121–138. https://doi.org/10.1037//0096-1523.29.1.121

How to cite this article: Abbasi, H., Henare, D., Kadel, H., & Schubö, A. (2022). Selection history and task predictability determine the precision expectations in attentional control. *Psychophysiology*, *00*, e14151. https://doi.org/10.1111/psyp.14151

Study III

Meibodi, N., Abbasi, H., Schubö, A., & Endres, D. M. (2021). A model of selection history in visual attention. *In Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 43, No. 43)

UC Merced
Proceedings of the Annual Meeting of the Cognitive Science Society

Title
A model of selection history in visual attention

Permalink
https://escholarship.org/uc/item/3m33h9h7

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 43(43)

ISSN
1069-7977

Authors
Meibodi, Neda
Abbasi, Hossein
Schubö, Anna
et al.

Publication Date
2021

Peer reviewed

A model of selection history in visual attention

Neda Meibodi (meibodi@uni-marburg.de)

Hossein Abbasi (hossein.abbasi@uni-marburg.de)

Anna Schubö (schuboe@uni-marburg.de)

Dominik Endres (dominik.endres@uni-marburg.de)

Department of Psychology, Philipps-University Marburg, Gutenbergstrasse 18,
35032 Marburg, Germany

Abstract

Attention can be biased by the previous learning and experience. We present an algorithmic-level model of this bias in visual attention that predicts quantitatively how bottom-up, top-down and selection history compete to control attention. In the model, the output of saliency maps as bottom-up guidance interacts with a history map that encodes learning effects and a top-down task control to prioritize visual features. We test the model on a reaction-time (RT) data set from the experiment presented in (Feldmann-Wüstefeld, Uengoer, & Schubö, 2015). The model accurately predicts parameters of reaction time distributions from an integrated priority map that is comprised of an optimal, weighted combination of separate maps. Analysis of the weights confirms learning history effects on attention guidance.

Keywords: Visual attention; Selection history; Integrated priority map; Self information maximization; Feature integrated theory; Ex-Gaussian distribution

Introduction

Selective visual attention is a brain function that filters irrelevant sensory inputs to facilitate focusing on relevant items. Bottom-up and top-down mechanisms have traditionally been proposed to control the process of attention guidance. Object saliency and environment features shape the attentional process in a bottom-up manner while the top-down process is mostly controlled by observer intentions and preferences.

In addition to top-down and bottom-up contributions also ‘selection history’ can play a significant role in guiding attention toward a specific target (Theeuwes, 2019). Selection history (as a third category of attentional deployment) comes into play when an object is emphasized just because of previous attendance in the same context (Awh, Belopolsky, & Theeuwes, 2012). To clarify the distinction between top-down guidance and selection history, Theeuwes argued that selection history is a fast, effortless, and automatic version of attention control while top-down selection is slow, effortful, and controlled (Theeuwes, 2018).

One special form of selection history has been investigated in (Feldmann-Wüstefeld et al., 2015; Kadel, Feldmann-Wüstefeld, & Schubö, 2017; Henare, Kadel, & Schubö, 2020). These studies combined an associative learning task with a visual search task. The result showed that observers attend more to a stimulus which was predictive in the preceding feature discrimination task. Considering to what extent selection history can be suppressed by top-down process, Kadel et al. (2017) tested three different top-down-influenced modes of task preparations such as pretrial task cuing. As their results showed, attentional biases induced by selection history persisted despite the task preparation.

An integrated priority map was proposed by Awh et al. as a theoretical framework to explain how selection history and other factors of attention guidance interact (Awh et al., 2012; Theeuwes, 2019). Priority maps have been successfully employed by many authors (Fecteau & Munoz, 2006; Zelinsky & Bisley, 2015; Klink, Jentgens, & Lorteije, 2014; Todd & Manaligod, 2017; Veale, Hafed, & Yoshida, 2017; Chelazzi et al., 2014) to explain the result of the processes which shape attention. In a review, Klink et al. (2014) summarized how goal-driven and stimulus-driven maps in cortex combine with a value-based map in midbrain. This combination results in a priority map for the frontal eye fields.

Stimulus-driven (bottom-up) models of attention were developed early on (Itti, Koch, & Niebur, 1998). These models tend to ignore the effects of selection history, task or training (Itti & Borji, 2015). Itti et al. (1998) implemented feature integration theory (three feature maps including color, intensity and orientation), winner-take-all, inhibition of return and a normalization method to model visual attention in a bottom-up manner. Veale et al. (2017) validated a neural implementation of Itti’s model. In another bottom-up model, Bruce and Tsotsos (2006, 2009) –using self information maximization ($-\log(p(x))$), where x is a feature – proposed a computational model of saliency that is called ‘Attention based on Information Maximization (AIM)’, because attention is attracted by surprising, i.e. potentially informative, regions of an image. Furthermore, thanks to deep learning advances, there has been recent progress in deep visual saliency models (Borji, 2019).

Beside above mentioned models, Itti and Borji (2015) reviewed more than 50 computational bottom-up models. They also reviewed some computational top-down models. Such models (Navalpakkam & Itti, 2005; Hwang, Higgins, & Pomplun, 2009; Borji, Sihite, & Itti, 2014) are less well researched than saliency models, which might be due to the fact that they require information not available from the stimulus. There are also some models on how bottom-up and top-down work together in attentional guidance (Chikkerur, Serre, Tan, & Poggio, 2010; Kimura et al., 2008). Chikkerur et al. (2010) used a Bayesian framework to explain how a combination of bottom-up and top-down attentional guidance work together in cortex.

Despite substantial progress in building models of attention, there are still many open questions. Selection history has hardly been modeled. One exception is Tseng et al.'s model of the influence of inter-trial priming – a type of selection history effect – on attention guidance (Tseng, Glaser, Caddigan, & Lleras, 2014). They implemented a Ratcliff-type diffusion model (Ratcliff, 1978) for a 2-forced-choice task and showed that the history can affect Ratcliff diffusion model parameters.

In this paper we introduce an algorithmic-level model (in the sense of Marr (1982)) to show how bottom-up, top-down and selection history compete against each other to guide visual attention toward a specific target. By selection history here we mean the effect of learning from previous experience on the current task (see (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Henare et al., 2020)). The model comprises priority maps to integrate goal-driven, saliency-based and history-related biases in a winner-take-all manner. Bottom-up guidance, feature maps and subsequently saliency maps are made based on 'feature integration theory' (Treisman & Gelade, 1980) and 'self information maximization' (AIM) (Bruce & Tsotsos, 2009). To reflect the effect of selection history and learning in the model, a history map contributes to the integrated priority map. Finally, task-relevant information controls the map integration weights that generate predictions for responses and response times. These integration weights are our model for the top-down influences. We test this model on a behavioral database from an experiment by Feldmann-Wüstefeld et al. (2015). The model can predict the reaction time distribution parameters for each participant and also across the experimental groups. To find the best distribution of reaction times, several probability density functions are compared maximizing log-likelihood and the best fitting one – an ex-Gaussian distribution (Matzke & Wagenmakers, 2009)– is used in the model.

Materials and methods

Experiment

The data used in this study comes from the first experiment of Feldmann-Wüstefeld et al. (2015). They investigated the impact of associative learning on covert selective visual attention. The experiment consisted of a 'practice' and a 'main' phase, in which two types of tasks (learning and search) were performed. A central fixation cross was presented on the screen, which was then surrounded by eight different elements on an imaginary circle (Figure 1). 28 participants were divided randomly into 2 different groups, namely 'color group' and 'shape group'. They were first naive about their group membership, but had to learn it on a trial and error basis in the practice phase.

In the 'practice phase', participants had to learn that either color or shape was the response relevant dimension in this learning task (see Figure 1A). Members of the color group had to report the color of the color singleton (blue or green), whereas members of the shape group had to respond to the shape of the shape singleton (triangle or pentagon). They had to use their left hands to press one of two buttons that were placed on the left side of the response pad. Auditory feedback indicated whether they pressed the incorrect key.

In the 'main phase' a second visual search task was added, and participants performed both tasks in random order. In the search task (Figure 1B), all participants had to report the orientation of a line presented inside a diamond shape target. In half of the trials, a response-irrelevant red circle was presented as distractor. Participants used their right hand to press one of two buttons on the right side of the pad to indicate the line orientation (horizontal versus vertical).

The results of this study showed that the history of selection acquired in the learning task affected the participants' performance in the search task. Stimuli that were predictive of the relevant dimension in the learning task biased attention in the visual search task. The authors suggested that the participants' history of either shape or color selection in the practice phase had resulted in a selection history bias.

We presented a model of this selection history bias in the current study based on the behavioral data from the main phase, which comprises at total of 28672 trials across all participants. More details about the experiment can be found in (Feldmann-Wüstefeld et al., 2015).

The Algorithmic Model

Based on the theoretical considerations outlined in the introduction and a preliminary data analysis, we assembled an algorithmic-level model to explain how top-down and bottom-up influences competitively interact with visual selection history to guide attention toward a specific stimulus. The results of this preliminary analysis, that was aimed at determining experimental factors influencing responses and reaction times, are not shown here for space constraints. Inspired by the integrated priority maps in (Awh et al., 2012), we used a 'history map' reflecting the influence of selection history on current attention deployment, see Figure 2. Additionally, there is an overall saliency map for bottom-up influences. How these maps combine into an integrated priority map is controlled by the task in a top-down fashion. Fig-

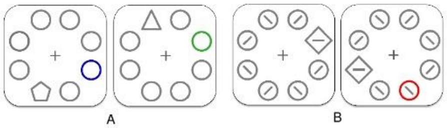


Figure 1: Learning task (A): Participants in the color group had to respond to the color (green vs. blue) and participants in the shape group had to respond to the shape (pentagon vs. triangle). Search task (B): The orientation (horizontal vs. vertical) of the line embedded in the diamond had to be reported. Distractor-absent trial (left). Distractor-present trial (right).

ure 2 also shows how the output of the integrated priority map feeds into a two-part neural network that predicts ex-Gaussian distribution parameters (Luce, 2008) of reaction times (left exit path in the figure) and response likelihoods (the right exit path).

The input stage of the model is based on feature-integration theory (Treisman & Gelade, 1980). The model extracts three types of features (color, shape and orientation) and feature maps –as shown in Figure 2– are computed. In the next processing step, saliency maps that model the effect of bottom-up control on visual attention (Koch & Ullman, 1985) are formed from the feature maps. Shannon's measure of Self-Information is applied, similar to Attention Based on Information Maximization (Bruce & Tsotsos, 2009), to compute saliency maps. Eq (1) and Eq (2) show the actual calculations behind map computation. Feature maps are $M \times N \times K$ vectors where M is the number of trials, N is the number of objects in each trial and K is the number of distinct values that each feature can take on, i.e. we are using 1-out-of-K encoding for the features, with the value 1 indicating which feature value is present. In the current experiment $M = 1024$ (for each participants), $N = 8$ and $K = 4$. Figure 3 illustrates the method of building feature maps for some example trials. For all trials, we take the feature maps f_i for $i \in \{color, shape, orientation\}$ and compute the self-information X_i:

$$\forall k : X_i[k] = -log\left(\sum_{n=1}^{N} f_i[n][k]/N\right) \tag{1}$$

which yields the saliency of all trials $s_i[n]$:

$$\forall n : s_i[n] = X_i\left[\arg\max_{k}(f_i[n][k])\right] \tag{2}$$

where, due to the 1-of-K feature encoding, we can use *argmax* to pick the self-information corresponding to the current feature value.

Saliency maps s_i are fed into the integrated priority map along with history information (h) to compete in a soft winner-take-all model (Theeuwes, 2019) for the predicted response target. Selection history, the third category of attentional guidance (Awh et al., 2012), carries the effect of learning (participants learned about color or shape in our experiment) into the priority map (p):

$$\forall m,n : p[m][n] = \operatorname{soft}\max_{n}\left(\sum_{i}\left(w_{s_i} * s_i[m][n]\right) + w_h * h[m][n]\right) \tag{3}$$

The weights (w_h for history and w_{s_i} for $i \in \{color, shape, orientation\}$) are used to combine the history map and the saliency maps and reflect the effect of the task in a top-down manner. The softmax function is used to ensure that the winning location receives the most attention while keeping the map interpretable as a probability distribution. In our model, Eq 3 can be interpreted as the first layer of a (two-layer) neural network. The second layer is a (linear) mapping from the integrated priority map to reaction time distribution parameters:

$$\forall m : d = \sum_{n=1}^{N}\left(p[m][n] * w_d\right) + B_d \tag{4}$$

When w and B are weights and biases of ex-Gaussian distribution parameters' for $d[m] \in (\mu[m], \sigma[m], \tau[m])$.

We also compute a 1-out-of-K representation of the target information ($g[m][n]$ in Eq 5, see also Figure 3) which is used for machine-learning the weights with which the history map and the saliency maps are combined. The weights (w_h, w_{s_i} and w_d) for a task are determined by maximizing the log of the joint distribution of the reaction times (RT), the target g under the distribution predicted by the integrated priority map and the prior distributions over the model parameters δ:

$$\begin{aligned} L &= \sum_{m=1}^{M} \log\left(ExG\left(RT[m] \,|\, \mu[m], \sigma[m], \tau[m]\right)\right) \\ &+ \left(\sum_{m=1}^{M}\sum_{n=1}^{N} \log(p[m][n]) * g[m][n]\right) + \delta \end{aligned} \tag{5}$$

where ExG is ex-Gaussian distribution function. δ is computed as the sum of the logs of the following prior distributions:

$$\begin{aligned} w &\sim \mathcal{N}(0.0, 1.0) \\ B_\mu &\sim \mathcal{N}(600.0, 100.0) \\ B_{\sigma^2} &\sim \mathcal{N}(75.0, 4.0) \\ B_\tau &\sim \mathcal{N}(200.0, 20.0) \end{aligned} \tag{6}$$

Mean and standard deviation of these distributions are selected in a way that matches results from similar experiments (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017). To find the weights and biases that maximize the joint probability (Eq 5), we draw random initial values from these distributions and then optimize using Python 3.7.6, PyTorch 1.6.0 and Adam optimizer with learning rate 0.2. Code and training data for the models can be found here: `http://dx.doi.org/10.17192/fdr/64.2`

Results and Discussion

To investigate how selection history quantitatively influences attentional guidance, three versions of the model with different history maps are tested. In the first version, the history map contains the response-relevant features in the learning phase (blue and green for the color group, triangle and pentagon for the shape group). In the second version of the model, the history map includes all color singletons (for participants in the color group) and all shape singletons (for participants in the shape group). The assumption is that the participants have learned response-predictiveness on the dimensional level (color or shape), not on the level of single features

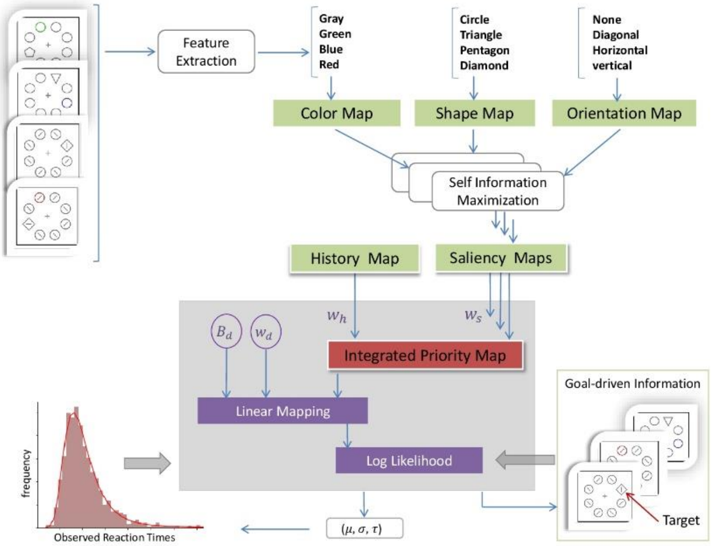


Figure 2: An overview of the algorithmic model. The blue arrows show the direction of data flow from visual input to response and gray arrows show the direction of feedback. w_s, w_h and w_d are map weights. w_s has three elements for color, shape and orientation. w_d has also three elements for distribution parameters(μ, σ, τ). B_d is distribution parameters' bias containing B_μ, B_σ and B_τ.

(such as green or blue). So not only blue, green, triangle and pentagon but also red and diamond are included. In the third version we exclude the history map from the model testing the assumption that only top-down and bottom-up guidance direct attention. To compare these versions of the model, we use a Laplace-approximation. We compute a second-order approximation of the marginal log-probability of the data given the different models' assumptions. We employ these log-probabilites for two Bayesian model comparisons (Bishop, 2006; Barber, 2012; Endres, Chiovetto, & Giese, 2013): fitting one model per participant, and one model per group. In both cases, a model that includes a history map and maps for those features that were predictive during the learning phase is at least 10^{20} as probable as the alternatives. For more details about the model evidences see Figure 4.

Under the assumption that there is a linear mapping from the priority map to the reaction time distribution parameters, the model machine-learns to predict the history map weight (w_h), saliency map weights (w_s) and also the distribution parameters weights and biases (w_d, B_d) (see Figure 2). To compare the weights and also to see how they vary between the color and the shape group see Figure 5, which shows the weights for model version one.

As can be seen in Figure 5, the 'history map' has a higher weight in the color group than in the shape group: to solve the learning task, the color group model has to rely on its learning history features (blue and green) in half of the trials, i.e. in the learning task. Although these colors could be found in the 'color map' as well, there is another color (red) in this map which is task-irrelevant and has to be suppressed. This may be the reason for the increased attention capture by the red distractor in color group members which is reported in (Feldmann-Wüstefeld et al., 2015).

For the search task, a high orientation weight is employed by the color group model, since this task can be solved by spotting an orientation singleton, cf. Figure 1, B.

In contrast, the shape group model can afford to rely less on its 'history map' because the items in its history (triangle and pentagon) exist in the 'shape map' too (triangle, pentagon and diamond), and there is no shape distractor. Therefore, by using a high shape map weight, both the learning task can be solved, and attention can be guided to the shape singleton containing the target in the search task (diamond).

To summarize, the weight of the 'orientation map' is larger in the color group than in the shape group, indicating that the color group model employs orientation saliency in the search task. Using orientation saliency, it does not need to attend to the shape singleton in the search task. However, the shape group model focuses on the 'shape map' which is response-relevant in both tasks.

Also, the weight of the 'color map' was higher in the color group than in the shape group model, since the latter can ig-

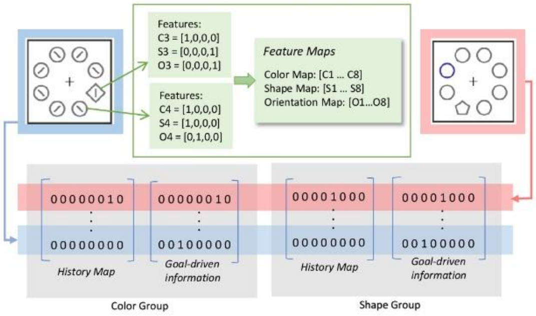


Figure 3: Feature maps, history map and goal-driven information for two random trials. We use 1-out-of-K encoding for the feature vectors, i.e. all components but one are zero. The nonzero component indicates the feature value (see the green box). In each row of history map the location of learned feature is marked. In the target (goal-driven) information the location of response-relevant feature is marked.

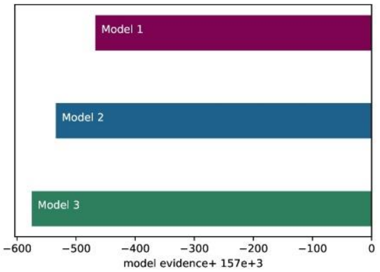


Figure 4: Model comparison. We computed a Laplace-approximation to the Bayesian model evidence across participants. Bigger evidence is better. Model version one, whose history map contains relevant features, scores best. For model descriptions, see text.

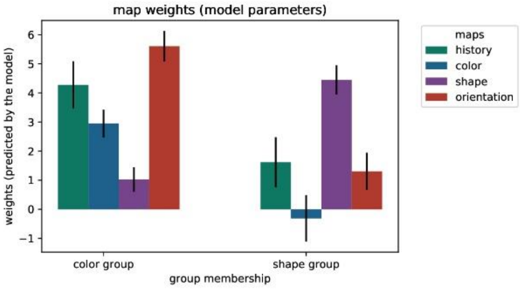


Figure 5: Map weights. For both color group and shape group, optimal map weights for model one are shown. A higher weight means a stronger influence of the corresponding map onto the response and reaction time. The error bars represent the standard deviations of the posterior, i.e. standard errors.

nore color altogether.

The model approximates the reaction time distribution parameters (μ, σ, τ) very well (as can be seen in Figure 6). To quantify how close the model-predicted distributions are to the best fit to the data, we evaluate an approximation to the KullbackLeibler (KL) divergence (Bishop, 2006):

$$KL(p||q) = \int p(RT) \log\left(\frac{p(RT)}{q(RT)}\right) dRT \tag{7}$$

$$\approx \frac{1}{M}\sum_{m=1}^{M} \log p(RT_m) - \frac{1}{M}\sum_{m=1}^{M} \log q(RT_m)$$

where RT_m is the reaction time in trial m, p(RT) and q(RT) are model-predicted and best-fit distributions respectively. For both color and shape group RTs, we find $KL(p||q) \leq 10^{-4}$ which is very close to the minimal possible value.

Conclusion

We presented a model of selection history in visual attention. The model implements the idea that selection history has a role in attention guidance as claimed by Feldmann-Wüstefeld et al. (2015). We compared different versions of the model and the results show that the one which includes selection history, beside bottom-up and top-down control, is best suited for a quantitative description of the behavioral (RT) results. Our model successfully implements an integrated priority map as proposed by Awh et al. (2012). To determine if this integrated priority map approach is indeed the best description of human behavior, future research needs to investigate non-integrated alternatives. Furthermore, as humans use their attention system in a large variety of situations, a model of task switching needs to be added, rather than training one model per task. The search for such alternatives might be facilitated if we knew what the attentional system is actually trying to achieve on a quantitative level. This is a question situated on the 'computational level' (Marr, 1982). Therefore, we intend to build a computational model in a Bayesian/optimal feedback control framework for both ideal and non-ideal observer-actors. Stochastic evidence accumulation approaches – that have been applied in some other models such as Race Models (Mordkoff & Yantis, 1991) and Drift Diffusion models (Luce, 2008) – might be useful to this end. Another interesting avenue of investigation, which would help in constraining the model, would be the addition of physiological variables. For example, adding EEG signals to disentangle target and related sub-processes (such as enhanced target processing or distractor suppression) would shed further light on attentional guidance processes.

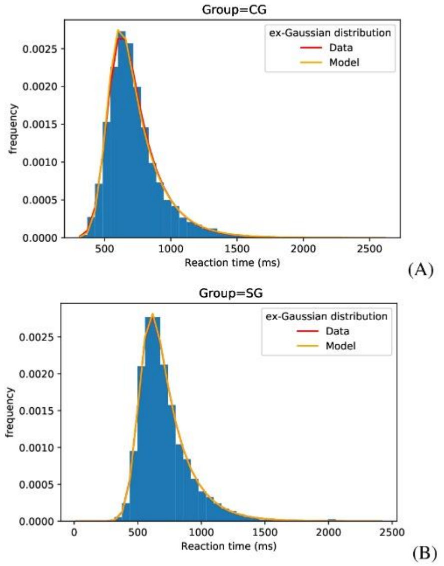


Figure 6: Ex-Gaussian distributions of reaction times. Best fits to the data (red) and model predicted distributions (orange) for participants in (A): color group (CG). (B): shape group (SG).

Acknowledgments

This work was supported by the DFG SFB-TRR 135 "Cardinal Mechanisms of Perception", projects C6 and B3, and "The Adaptive Mind", funded by the Excellence Program of the Hessian Ministry for Science and the Arts. We thank Sara Müller for her contributions to earlier versions of the model.

References

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. Retrieved from `http://dx.doi.org/10.1016/j.tics.2012.06.010`

Barber, D. (2012). *Bayesian Reasoning and Machine Learning*. Cambridge: Cambridge University Press. Retrieved from `http://ebooks.cambridge.org/ref/id/CBO9780511804779`

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

Borji, A. (2019). *Saliency Prediction in the Deep Learning Era: Successes, Limitations, and Future Challenges*. Retrieved from `https://arxiv.org/abs/1810.03716`

Borji, A., Sihite, D. N., & Itti, L. (2014). What/Where to Look Next? Modeling Top-down Visual Attention in Complex Interactive Environments. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *44*(5), 523–538. Retrieved from `http://ilab.usc.edu/`

Bruce, N. D., & Tsotsos, J. K. (2006). Saliency based on information maximization. *Advances in Neural Information Processing Systems*, *18*, 155–162. Retrieved from `http://books.nips.cc/papers/files/nips18/NIPS2005_0081.bib`

Bruce, N. D., & Tsotsos, J. K. (2009). Saliency , attention , and visual search: An information theoretic approach. *Journal of Vision*, *9*(3), 1–24. Retrieved from `https://doi.org/10.1167/9.3.5`

Chelazzi, L., Eštočinová, J., Calletti, R., Gerfo, E. L., Sani, I., Libera, C. D., & Santandrea, E. (2014). Altering spatial priority maps via reward-based learning. *Journal of Neuroscience*, *34*(25), 8594–8604. Retrieved from `http://doi/10.1523/JNEUROSCI.0277-14.2014`

Chikkerur, S., Serre, T., Tan, C., & Poggio, T. (2010). What and where: A Bayesian inference theory of attention. *Vision Research*, *50*(22), 2233–2247. Retrieved from `http://dx.doi.org/10.1016/j.visres.2010.05.013`

Endres, D. M., Chiovetto, E., & Giese, M. A. (2013). Model selection for the extraction of movement primitives. *Frontiers in Computational Neuroscience*, *7*, 185. Retrieved from `https://doi.org/10.3389/fncom.2013.00185`

Fecteau, J. H., & Munoz, D. P. (2006). *Salience, relevance, and firing: a priority map for target selection* (Vol. 10) (No. 8). Retrieved from `https://doi.org/10.1016/j.tics.2006.06.011`

Feldmann-Wüstefeld, T., Uengoer, M., & Schubö, A. (2015). You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention. *Psychophysiology*, *52*(11), 1483–1497. Retrieved from `https://doi.org/10.1111/psyp.12514`

Henare, D. T., Kadel, H., & Schubö, A. (2020). Voluntary Control of Task Selection Does Not Eliminate the Impact of Selection History on Attention. *Journal of Cognitive Neuroscience*, *32*(11), 2159–2177. Retrieved from `https://doi/abs/10.1162/jocn_a_01609`

Hwang, A. D., Higgins, E. C., & Pomplun, M. (2009). A model of top-down attentional control during visual search in complex scenes. *Journal of Vision*, *9*(5), 1–18. Retrieved from `https://doi.org/10.1167/9.5.25`

Itti, L., & Borji, A. (2015). *Computational models: Bottom-up and top-down aspects*. Retrieved from `http://arxiv.org/abs/1510.07748`

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliancy-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *20*(11), 1254 – 1259. Retrieved from `https://doi.org/10.1109/34.730558`

Kadel, H., Feldmann-Wüstefeld, T., & Schubö, A. (2017). Selection history alters attentional filter settings persistently and beyond top-down control. *Psychophysiology*, *54*(5), 736–754. Retrieved from `https://doi.org/10.1111/psyp.12830`

Kimura, A., Pang, D., Takeuchi, T., Miyazato, K., Yamato, J., & Kashino, K. (2008). *A stochastic model of human visual attention with a dynamic Bayesian network.* Retrieved from `http://arxiv.org/abs/1004.0085`

Klink, P. C., Jentgens, P., & Lorteije, J. A. M. (2014). Priority Maps Explain the Roles of Value, Attention, and Salience in Goal-Oriented Behavior. *Journal of Neuroscience*, *34*(42), 13867–13869. Retrieved from `https://doi.org/10.1523/JNEUROSCI.3249-14.2014`

Koch, C., & Ullman, S. (1985). Shifts in selective visual attention: Towards the underlying neural circuitry. *Human Neurobiology*, *4*(4), 219–227. Retrieved from `https://doi.org/10.1007/978-94-009-3833-5`

Luce, R. D. (2008). *Response Times: Their Role in Inferring Elementary Mental Organization*. New York: Oxford University Press.

Marr, D. (1982). *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. W. H. Freeman and Company.

Matzke, D., & Wagenmakers, E. J. (2009). Psychological interpretation of the ex-gaussian and shifted wald parameters: A diffusion model analysis. *Psychonomic Bulletin and Review*, *16*(5), 798–817. Retrieved from `https://doi.org/10.3758/PBR.16.5.798%0A`

Mordkoff, J. T., & Yantis, S. (1991). An Interactive Race Model of Divided Attention. *Journal of Experimental Psychology: Human Perception and Performance*, *17*(2), 520–538. Retrieved from `https://doi.org/10.1037//0096-1523.17.2.520`

Navalpakkam, V., & Itti, L. (2005). Modeling the influence of task on attention. *Vision Research*, *45*(2), 205–231. Retrieved from `https://doi.org/10.1016/j.visres.2004.07.042`

Ratcliff, R. (1978). A Theory of Memory Retreival. *Psychological Review*, *85*(2), 59–108. Retrieved from `https://doi/10.1037/0033-295X.85.2.59`

Theeuwes, J. (2018). Visual Selection: Usually Fast and Automatic; Seldom Slow and Volitional. *Journal of Cognition*, *1*(1), 1–15. Retrieved from `https://doi.org/10.5334/joc.13`

Theeuwes, J. (2019). Goal-driven, stimulus-driven, and history-driven selection. *Current Opinion in Psychology*, *29*, 97–101. Retrieved from `https://doi.org/10.1016/j.copsyc.2018.12.024`

Todd, R. M., & Manaligod, M. G. (2017). Implicit guidance of attention: The priority state space framework. *Elsevier*, *102*, 121–138. Retrieved from `http://dx.doi.org/10.1016/j.cortex.2017.08.001`

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. Retrieved from `https://doi.org/10.1016/0010-0285(80)90005-5`

Tseng, Y. C., Glaser, J. I., Caddigan, E., & Lleras, A. (2014). Modeling the effect of selection history on pop-out visual search. *PLoS ONE*, *9*(3). Retrieved from `https://doi.org/10.1371/journal.pone.0089996`

Veale, R., Hafed, Z. M., & Yoshida, M. (2017). How is visual salience computed in the brain? Insights from behaviour, neurobiology and modeling. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1714). Retrieved from `https://doi.org/10.1098/rstb.2016.0113`

Zelinsky, G. J., & Bisley, J. W. (2015). The what, where, and why of priority maps and their interactions with visual working memory. *Annals of the New York Academy of Sciences*, *1339*(1), 154–164. Retrieved from `https://doi.org/10.1111/nyas.12606`

Study IV

Abbasi, H., Dötsch, D., & Schubö, A. (submitted). I see what you see: EEG correlates of attentional capture by a partner’s target in joint action

Running head: Attentional capture in joint action

Title: I see what you see: EEG correlates of attentional capture by a partner target in joint action

Authors:

Hossein Abbasi

Dominik Dötsch

Anna Schubö

Affiliations:

Cognitive Neuroscience of Perception and Action, Philipps-University of Marburg, Germany

Corresponding author:

Hossein Abbasi

Philipps-University of Marburg
Experimental and Biological Psychology
Gutenbergstraße 18
35037 Marburg
Hossein.abbasi@uni-marburg.de

Acknowledgments

This research was supported by the Deutsche Forschungsgemeinschaft (German Research Foundation), International Research Training Group (IRTG) 1901, "The Brain in Action", project number 220482592.

Abstract

In joint action, agents are assumed to represent their partner's task to optimize joint performance. However, the neurophysiological processes underlying the processing of the partner's task have not been widely investigated. Pairs of participants were asked to respond to a joint version of a visual search task in either a cooperative or a competitive social context. During the task, one agent's neural activity was recorded using electroencephalography (EEG). Our behavioral results showed impeded search performance when the partner target was presented. Furthermore, EEG time-frequency results showed that the partner target induced a negative parieto-occipital alpha-lateralization, indicating that it captured attention, when the agent target was absent. The parieto-occipital alpha-lateralization index was negative for laterally presented partner targets in the cooperative and positive in the competitive social context, indicative of attentional capture in the cooperative condition and suppression of the partner target in the competitive condition. In sum, our study showed that humans tune their attentional processing toward a partner target in a joint action task. This attentional tuning was shown to be affected by social context and the presence of the agent's own target.

Keywords: partner target representation, visual attention, alpha-band power, attentional capture, social context

Introduction

In everyday life, sharing tasks with others is ubiquitous, for example, when coordinating to move a heavy table. This kind of social interaction in which people coordinate their actions both temporally and spatially to accomplish a task is called joint action (Sebanz, Bekkering, & Knoblich, 2006). Successful performance in a shared task highly depends on the cognitive representation of the partner's task goals and on directing the attention to a common point of reference in space, which is often referred to as joint attention (Michael, Sebanz, & Knoblich, 2016). Co-acting participants in joint action tasks need to identify not only their own and their partner's relevant objects, but they also need to be mutually aware of the fact that they both attend the same event (Kourtis, Knoblich, Woźniak, & Sebanz, 2014; Freundlieb, Sebanz, & Kovács, 2017). Several studies have shown that stimuli referring to a partner's task can activate similar action tendencies in co-acting agents, which need to be suppressed if it is not actually the agent's turn to act (de Bruijn, Miedl, & Bekkering, 2008; Sebanz, Rebbechi, Knoblich, Prinz & Frith, 2007; Sebanz, Knoblich, Prinz, & Wascher, 2006; Tsai, Kuo, Jing, Hung, & Tzeng, 2006).

For example, Sebanz, Knoblich, & Prinz (2003) asked participants to respond to a joint version of the Simon task (Simon, 1969), a spatial compatibility task in which two cooperating agents respond to targets in one of two colors using left and right hand-side button presses. The targets contained task-irrelevant spatial information, e.g. the agent target pointed to the partner's (incompatible) or to the agent's (compatible) sitting location. Participants performed the task either individually responding to only one color (single condition) or together with a partner, each responding to one color (joint condition). In the joint condition responses were faster in the compatible than in the incompatible trials (joint Simon effect). Importantly, this effect was not observed in the single condition (see also Sebanz et al., 2006; Tsai et al., 2006). These findings indicated that, in the joint condition, participants formed a cognitive representation of their own and their partner's task which included a representation of the spatial dimension of the responses. The stimulus pointing to the location of the partner, which was task-irrelevant for the agent, activated the agent's representation of the partner's action and this co-representation of the partner's action interfered with the agent's own action representation. This interference reduced the efficiency of the agent's task performance. Critically, some studies have shown that even the presence of non-human or passive co-actors can induce the joint Simon effect (Dolk et al., 2011, 2013, 2014; Dittrich, Rothe, & Klauer, 2012; Lien, Pedersen, & Proctor, 2016). Dolk and colleagues suggested that the mere presence of a non-social attention-attracting salient event would be enough to establish a reference frame to introduce the coding of alternative actions. As an explanation, performing a task while sitting next to a (social or non-social) co-actor renders the horizontal dimension more salient than when doing the same task individually. This allows participants to code their responses as referenced to the position of the co-actor. As a consequence, participants code their own action (e.g. button press) as left or right which results in action interference when the response code and stimulus spatial features are dissimilar (referential coding account; Dolk et al., 2011, 2013, 2014).

Further evidence for differences between processing of the partner target and a distractor comes from a study by Atmaca, Sebanz, & Knoblich (2011): When partners shared a task, response times (RTs) were shorter when an agent target was flanked by neutral flankers compared to when it was flanked by the partner target. The authors speculated that the agents represented the partner's task in addition to their own task, which resulted in response interference. Similar findings have been reported in a recent study when participants were asked to report whether they saw their assigned font color on the screen. The stimuli were some color names which could be written in a font color assigned to the agent, the partner, or none of them (Saunders, Melcher, & van Zoest, 2019). The agents performed the task alongside a human or non-human (computer) co-actor. As their results showed, responses were slower when the displayed word was semantically associated with the agent's own target or with the partner target compared to when the displayed word was semantically associated with the non-relevant color. According to the action co-representation account, this finding suggested that participants represent their partner's task in a similar manner as their own task and different from a non-relevant distractor. Crucially, this effect was also observed in the absence of a social partner, making it difficult to explain the findings by referring to social co-representation.

In addition to behavioral findings, neurophysiological evidence strengthens the claim that sharing a task with a partner triggers a tendency to perform the same action as the partner (Sebanz et al., 2006, 2007; Tsai et al., 2006). For example, in a no-go trial in a go/no-go task, parietal cortical regions of the agent show increased activity in a joint condition when the partner needs to act, compared to a single no-go condition (Sebanz et al., 2007). This finding indicates that the agent considers the partner's task even when the partner's task doesn't require any form of involvement. In an EEG study, Sebanz et al. (2006) observed a larger no-go P3 amplitude, an ERP component associated with response inhibition in no-go trials, in a joint setting compared to a single setting when no response of the agent was required (see also Tsai et al., 2006). As Sebanz et al. (2006) speculated, perceiving a stimulus which was action-relevant for the partner activates a representation of the partner's action which needs to be inhibited by the agent when it is the partner's turn to act.

Besides ERP components, alpha-band power changes have been studied in joint action tasks. A decrease of power in the frequency range of 10 – 12 Hz has been observed when participants engage in a movement coordination task compared to when no coordination is required (Naeem, Prasad, Watson, Kelso, 2012; Fitzpatrick, Mitchell, Schmidt, Kennedy, & Frazier, 2019). Furthermore, action observation has been shown to reduce posterior alpha-band power compared to when no action is observed (Hauswald, Tucciarelli, & Lingnau, 2018). Also responding to a shared target affects the pattern of alpha-band oscillations. In their study, Lachat, Hugueville, Lemaréchal, Conty, & George (2012) asked pairs of participants to look at either the same (i.e. joint attention condition) or different (i.e. single attention condition) targets while they were sitting face-to-face on each side of the experimental setup. Targets could be one (in joint condition) or two (in single condition) of the four LEDs which were placed on the lower hemifield of a circular hole border. The results showed reduced alpha-band power over the posterior regions in the joint compared to the single condition. Lachat et al. (2012) concluded that action coordination and mutual attentiveness were greater when partners attended the same point of reference in the space. Sharing the target resulted in a decrease of alpha-band power in the joint attention condition. Since the above findings reveal the role of alpha-band in attentional processes in single and shared tasks, we assumed that investigating alpha-band power in a shared visual search task will also reveal how the agent's attention is directed toward the partner target in different social contexts.

Social Context in Joint Action: Cooperation vs. Competition

Competition and cooperation in joint action are different types of interdependency that can lead to different behavior (Mendl, Fröber, & Dolk, 2018; Ruissen & de Bruijn, 2016; Colzato, de Bruijn, & Hommel, 2012; Hommel, Colzato, & van den Wildenberg, 2009). Higher interdependency between the agents typically increases the impact a partner's task has on the agent's performance. Ruissen & de Bruijn (2016) asked participants to play a game before the experiment started, either in a cooperative, competitive or individual mode. In the later experiment, participants performed a joint Simon task with neutral task instructions. Results showed that cooperation induced a larger joint Simon effect than competition and the individual mode (see also Colzato et al., 2012). A similar effect was observed by Hommel et al. (2009), who let participants perform a joint Simon task with a confederate. For half of the participants, the confederate showed friendly behavior and gave positive feedback to the participants (inducing a positive relationship). For the other half of the participants, the same confederate behaved "intimidatingly" and gave negative feedback. Participants who experienced a positive partner showed a larger joint Simon effect than participants who experienced a negative partner. Thus, agents who compete or are in a negative relationship don't integrate the partner's task to the same degree as agents who cooperate or who are in a positive relationship. A positive and cooperative relationship makes it more likely that agents represent their partners' task, although this might interfere with their own task representation and result in less efficient performance.

Task integration and segregation have been reflected in the neural activity in joint action tasks. In view of the above findings, the best strategy to perform a successful competitive task would be to ignore the partner's task as good as possible. This consideration was investigated by de Bruijn et al. (2008), who compared the EEG correlates of response inhibition in no-go trials in which the partner was supposed to respond (i.e. no-go P3) with activity in trials that required no response from any partner. Results showed that participants with unsuccessful performance (slow performance) showed smaller no-go P3 amplitudes in joint no-go than in no response trials, an effect which was not observed in the participants with successful performance. Furthermore, participants with unsuccessful performance showed larger error rates, indicating less successful response inhibition, in the incompatible compared to the compatible trials. These results showed that in a competitive joint action task, unsuccessful performance can be caused by attention capture by the partner target. A successful competitor, in contrast, would try to ignore or inhibit the partner's task to optimize the own task performance.

Rationale of the Present Study

The present study used a variant of the additional singleton task (Theeuwes, 1992) that was adapted to a joint action task setting to examine how agents deploy their attention in a visual search task performed alongside a partner in different social contexts. In the original additional singleton paradigm, participants searched for a target singleton which was presented together with a more salient but task-irrelevant distractor singleton shown in some of the trials. In single action performance, target responses are delayed in the presence of the distractor, which is considered a consequence of the distractor's potential to capture the observer's attention. In the present joint action paradigm, all colored stimuli were of equal luminance and of same visual salience. Search displays consisted of six gray and two colored stimuli. There were four colored stimuli in the experiment that were assigned different roles: one color identified the agent target, a second color the partner target, the two remaining colors were used for two non-relevant color distractors. The experiment followed two purposes: first, we wanted to examine to what extent the partner target would affect the agent's target response, and second, we were interested whether this effect was modulated by the social task context. To examine the impact of the partner target, we compared trials with the partner target to trials with a non-relevant color distractor. Since both color singletons were of equal salience, their distracting potential should be of equal size. If we observed difference in attention deployment, these cannot be attributable to differences in salience, but must result from differences in priority between the partner target and the non-relevant distractor. We hypothesized that the partner target would be considered of higher social value and would thus capture the agent's attention to a higher degree than the non-relevant distractor, resulting in slower and less accurate performance. Moreover, as attentional deployment is reflected in an alpha-band power decrease, we expect to see a negative lateralization of alpha-band power in trials with a partner target.

Furthermore, we manipulated the social context by encouraging competition or cooperation via instruction and feedback given during the task. We speculated that the agent would deploy some attention to the partner target in the cooperative condition, which should be reflected in a negative lateralization of alpha-band power relative to the partner target. In the competitive condition, in contrast, we assumed that the agent would suppress the partner target to perform better than the partner. We expected to see this suppression as a positive lateralization of alpha-band power.

Materials and Methods

Participants

48 female volunteers (mean age ± SD: 21.8 ± 2.4 years) naïve to the objective of the experiment were grouped into 24 pairs. All participants were right-handed (Edinburgh Handedness Inventory; Oldfield, 1971). All participants had normal or corrected-to-normal visual acuity and no color vision deficiencies (tested with Landolt rings for visual acuity, Ishihara's test for color vision; Binoptometer 3, Oculus, Germany). Participants gave written informed consent and received course credit for their participation.

Stimuli

Search displays contained eight stimuli arranged equidistantly on an imaginary circle (eccentricity of 5.7° of visual angle) around a central fixation cross (0.65°; RGB: 128, 128, 128; 45 cd/m² of luminance, measured 100 cm centrally in front of the screen with an LS-100 spectrometer, Konica Minolta, Tokyo, Japan) against a light grey background (RGB: 240, 240, 240; 97 cd/m²). Two of the stimuli were always colored, the remaining six were grey (RGB: 128, 128, 128; 45 cd/m²). One colored stimulus was presented on one of the two horizontal positions, the other on one of the two vertical positions. All stimuli had a diameter of 2.3°. Stimuli were Gabor patches, i.e. grated sinusoidal luminance modulations with a Gaussian envelope blending the colored patch gratings with the background (created with a tool by Mathôt, 2022; see Figure 1).

Four colored stimuli were used (Figure 1b): blue (RGB: 0, 148, 217), green (RGB: 0, 163, 0), orange (RGB: 242, 76, 0), and purple (RGB: 255, 0, 255). Assignment of stimuli colors to targets and non-relevant distractors was balanced across participant pairs. Luminance of all colored stimuli was identical (45 cd/m²). There were 96 stimulus orientations, varying from -66.5° to the left of the vertical axis to +66.5° to its right in steps of 0.4°. Over the course of the experiment, each stimulus was presented once in every orientation at the vertical positions and once in every orientation at the horizontal positions for all combinations of stimuli. Orientations in any specific trial were randomly selected according to this criterion. Grey stimuli orientations were randomly selected for every trial. The response screen was comprised of a striped grey semicircle on the light grey background (diameter 16.4°, width 1.5°; 45 cd/m²), which indicated the possible target orientations (see Figure 1c). There were two text cues (1.9° by 0.3°; 45 cd/m²): One cue in the middle of the semicircle indicated the participant who should respond ("right/left participant" in German), another underneath the semicircle could be clicked on by participants to indicate that no target was detected ("No target stimulus" in German).

Apparatus

Participants were seated side-by-side in comfortable chairs in a dimly lit, sound attenuated and electrically shielded room. Stimuli were presented on a 22-inch NT-TFT display (Syncmaster 2233, Samsung, Korea) with a 100 Hz refresh rate placed centrally in front of the EEG participant at a distance of 100 cm. The other participant was seated 60 cm to the left of the EEG participant at a 45° angle (Figure 1a). Stimulus presentation and the experimental procedure were controlled by E-Prime 2.0.8 (Psychology Software Tools, Inc., Sharpsburg, USA) running on a Windows 7 computer. Participants responded with their right hand using wired optical computer mice (Microsoft Corporation, Redmond, USA). Mouse button assignment was balanced across participant pairs.

EEG Recording

EEG data was recorded from one of the two participant (“the agent”) using 64 Ag/AgCl electrodes (actiCAP, Brain Products, Munich, Germany) according to the international 10-10 system. Horizontal and vertical electro-oculograms (EOGs) were also recorded from electrodes on the outer canthi of both eyes and above and below the left eye, respectively. For all electrodes, impedance was kept below 5 kΩ and during data recording all the electrodes were referenced to FCz. Data were recorded with a BrainAmp amplifier (Brain Products) at a sampling rate of 1000 Hz and filtered with a low cut-off filter of 0.016 Hz and a high cutoff filter of 250 Hz (-3 dB cutoff, Butterworth filter, 30dB/oct rolloff).

Post-Test Questionnaire

Participants rated the difficulty, pleasantness and competitiveness of the task. Participants also rated how difficult it was to detect their own target, as well as how often they detected the partner target. All ratings were based on 7-point Likert scales assessed separately for the cooperative and competitive conditions.

Procedure

All participant pairs took part in two sessions on the same day separated by at least four hours. In each session, they performed the task in one of the two social context settings (cooperation or competition). The session order was counterbalanced across participant pairs. Each session consisted of 12 blocks with 64 trials each. In 384 of 768 trials, the agent target was present. From these 384 trials, in 192 trials the agent target was presented together with the partner target and in the other 192 trials with a non-relevant colored distractor. In the remaining trials, the agent target was absent and a non-relevant distractor was presented together with the partner target or with another non-relevant distractor (192 trials each). Each stimulus combination was presented

16 times in every block, with positioning balanced so that every colored stimulus appeared at both horizontal and both vertical positions equally often. Display type order within each block was randomly selected.

Every trial started with the presentation of a central fixation cross, which remained on screen until search display offset. After 500 ms, the search display was presented for 200 ms. After that, the response screen, indicating possible orientations on striped semicircle, was presented and remained on screen until the agent had entered a response. Then, the response screen for the partner was presented and remained on screen until the partner had entered a response. This order was used for all participants so that the agent would not be influenced by the partner's response. To indicate a target orientation, participants moved the mouse cursor to the corresponding orientation on the response screen semicircle and confirmed their response with a mouse button click. If participants detected no target, they clicked on the "No target" text cue. After a blank screen presented for a random duration of 200 – 300 ms, a new trial started with the presentation of the central fixation cross (Fig. 1c).

At the end of each block, participants received different feedback depending on the social context: In the competitive condition, participants were shown the individual mean deviation of their orientation responses from their respective target orientations (in degrees) in the last block. Underneath, it was stated whose deviation from the target orientations was smaller in the last block ("Left/Right participant was better!" in German). In the cooperative condition, participants were shown the joint mean deviation from the target orientations in the last block, with a text feedback comparing the joint mean deviation from the target orientations in the last block to a (sham) comparison group of earlier participants ("Comparatively low/high deviation!" in German). In reality, the result of the sham comparison depended on whether the joint mean deviation from the target orientations exceeded 10°.

At the beginning of each session, participants performed a practice block of 64 trials. In the practice block, both the agent and the partner target were presented 16 times together, and 16 times each with a non-relevant colored distractor. In another 16, two non-relevant colored distractors were presented. In the practice block, stimuli were presented in one of eight orientations not used in the experiment (70° to -70° from the vertical in 20° steps). If one of the participants' accuracy of detecting their target was below 75%, the practice block was repeated.

Data Analysis

Behavioral data. Trials with correct target present and correct target absent responses were considered accurate response trials. If agents correctly reported the target orientation, the mouse cursor position at the time of the mouse click was converted into an angle relative to the central midline of the response semicircle. This angle was then subtracted from the target orientation angle to calculate the deviation of the orientation response. Mean absolute differences (in degrees) were calculated. Response times were calculated as the time between search display offset and the agent's mouse click on the response semicircle or on the "No target" button. Only trials with accurate responses were considered for the orientation responses, RTs and EEG analysis.

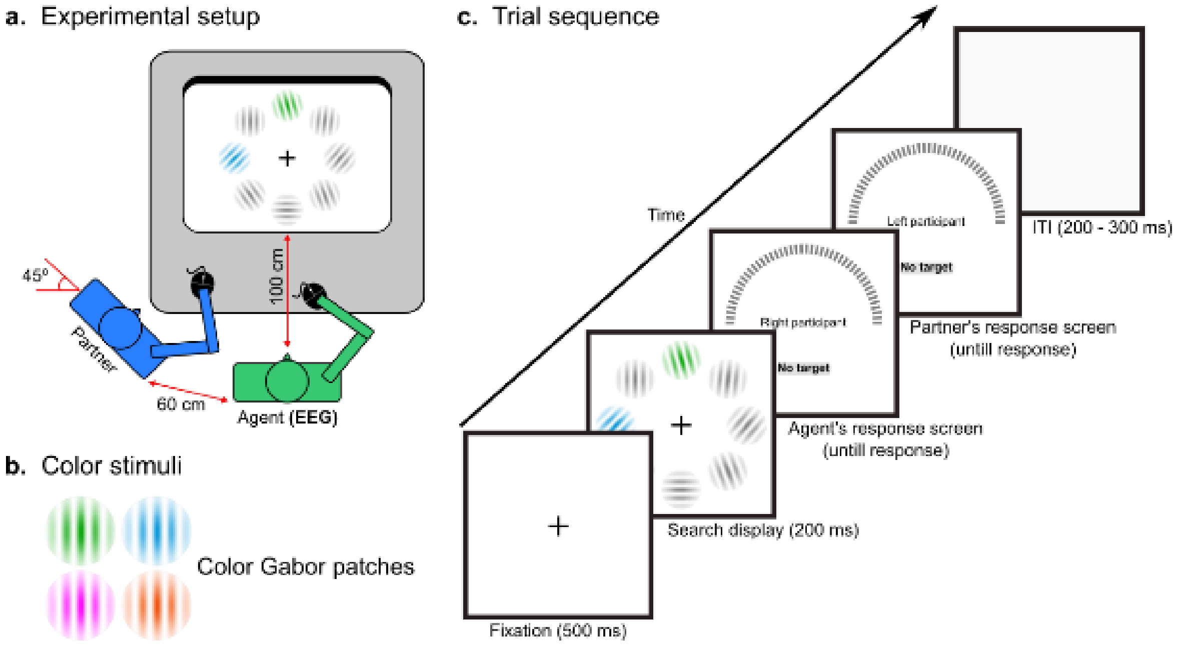


Figure 1. Experimental setup, stimuli and trial sequence: **a)** Schematic representation of the experimental setup. Participants were asked to report the orientation of their target using the mouse curser on the response screen. Each search display contained eight Gabor patches, arranged in such way that one colored item was on the vertical midline and one on the horizontal midline. Search displays always contained two colored items: either the agent target and the partner target, or the agent target and a non-relevant color distractor, or the partner target and one non-relevant color distractor, or two non-relevant color distractors. **b)** Gabor patches were green, blue, purple, orange or gray. The assignment of colors to the targets and non-relevant distractors was balanced across participant pairs. All color stimuli were matched in luminance. **c)** After search display presentation, the agent always responded before the partner. Participants moved the mouse cursor to report the orientation corresponding to their target on the response screen. In trials without a target, they had to click the "No target" response.

EEG pre-processing. Off-line EEG data analysis was performed using the MATLAB-based Fieldtrip toolbox (Oostenveld et al., 2011) and custom MATLAB R2019a (Mathworks, http://www.mathworks.com) scripts. EEG data were re-referenced to the average of all EEG electrodes and then filtered via a band-pass filter with bandwidth of 1-35 Hz. EEG data were epoched from -700 ms to +1500 ms relative to search display onset. Artifacts induced by eye movements were removed via an independent component analysis (ICA). The components representing eye movements over the pre-frontal region were manually identified using visual inspection and eliminated from the EEG data (same procedure used by Wildegger, van Ede, Woolrich, Gillebert, & Nobre, 2017). The rest of the components were back projected to constitute the EEG data (number of components projected out in the cooperative condition: 2.21 ± 0.59, and in the competitive condition: 2.25 ± 0.85, mean ± SD). Next, channels with activity > ±100 µV in the first 350 ms after stimulus onset in a trial were excluded.

Time-frequency analysis. Following our previous approach (Abbasi, Kadel, Hickey, & Schubö, 2022), pre-processed data were down-sampled to 250 Hz and re-epoched from -500 ms to +1500 ms relative to search display onset. A spectral analysis of the time series was performed using Fast Fourier transform (FFT) on the zero-padded data using a 250 ms Hanning window. The sliding window was shifted by 20 samples in every iteration over the time series data of each channel. Power estimation was calculated for frequencies between 2 and 32 Hz in steps of 1 Hz. Contra- and ipsilateral data were pooled separately for each participant and each condition (agent target lateral, partner target lateral or non-relevant distractor lateral). Then, we performed a normalization procedure [(Contralateral - Ipsilateral) / (Contralateral + Ipsilateral) × 100] to calculate the lateralization index as the percentage difference between contralateral and ipsilateral power (a similar approach to Wildegger et al., 2017 and Thut et al., 2006). The lateralization index helped to express the relative distribution of frequency bands in one value. This analysis was done over six parieto-occipital channels (PO7/8, PO3/4 & P7/8). A negative lateralization index in the range of alpha-band (i.e. alpha-lateralization index) shows decreased alpha-band power over the contralateral sites compared to the ipsilateral sites, indicating attentional deployment to a stimulus. A positive alpha-lateralization index shows increased alpha-band power over the contralateral sites compared to the ipsilateral sites, indicating suppression of a stimulus. The lateralization index was calculated separately for each trial type (target present vs. target absent), distractor type (partner target vs. non-relevant distractor) and the social context (cooperation vs. competition).

Statistical Analysis

Behavioral data. The agent's response times and response accuracies were analyzed with two 2 × 2 × 2 repeated measures analyses of variance (ANOVAs) with trial type (target present vs. target absent), distractor type (partner target vs. non-relevant distractor) and the social context (cooperation vs. competition) as within-subject factors. Orientation responses were analyzed with a 2 × 2 repeated measures ANOVA with distractor type (partner target vs. non-relevant distractor) and social context (cooperation vs. competition) as within-subject factors. Significant effects were followed up by paired-samples t-tests. All tests of significance were based upon an alpha error level of .05.

EEG data. To identify differences in the lateralization indices between conditions, we performed an analysis based on a cluster-based permutation test (Maris & Oostenveld, 2007) as implemented in the Fieldtrip toolbox (Oostenveld et al., 2011): In the first step, time-frequency bins were contrasted between conditions using paired sample t-tests. Then, temporally and/or spectrally adjacent bins which had p-values smaller than .05 were clustered. Note that a p-value smaller than .05 didn't mean a significant difference, but determined whether a sample could be part of a cluster or not. The summation of the t-values within each cluster was considered as the observed cluster t-value. In the second step, a permutation distribution of power matrices was created by collecting data across conditions and participants in a single set. Then, two subsets were created by randomly drawing half of the matrices irrespective of the actual conditions. Analogous to the first step, time-frequency bins were contrasted between subsets using a paired sample t-test, clusters were identified and cluster t-values were calculated. The largest cluster t-value was saved in a matrix to constitute a histogram of the test statistics. The procedure in the second step was repeated 10,000 times, which completed the histogram of the test statistics. Finally, we calculated the proportion of values in the histogram of the test statistics which were larger than the observed cluster t-value in the first step. If this proportion was smaller than the critical α-level of .05, then the power in the respective cluster was considered to differ significantly between two conditions. The T-maps in our results represent the observed t-values resulting from the first step of the cluster-based permutation test and the significant clusters are presented with a higher opacity.

When performing the cluster-based permutation test, we concentrated on the frequency range of 3 to 20 Hz over the time range of 500 ms after stimulus onset. Temporal resolution of the time-frequency analysis resulted in 26 time bins for each frequency from stimulus onset to 500 ms post-stimulus. We used permutation tests to compare the lateralization index in lateral partner target presentations with that of the lateral non-relevant distractor presentations. Furthermore, when the partner target or the non-relevant distractor was presented laterally, we compared the lateralization index in the competitive condition with the lateralization index in the cooperative condition.

Results

Behavioral Results

Response times (Fig. 2). RTs in search displays with the agent target present ($M \pm SD$ = 1950 ± 541 ms) were longer than responses in displays with the agent target absent (M = 1242 ± 215 ms), $F(1, 23) = 67.59$, $p < .001$, $\eta p^2 = .746$. RTs were also longer when search displays contained the partner target (M = 1617 ± 535 ms) compared to displays with a non-relevant distractor (M = 1575 ± 552 ms), $F(1, 23) = 19.95$, $p < .001$, $\eta p^2 = .465$. This effect was more pronounced when the agent target was absent ($M_{partner\ target\ present}$ = 1279 ± 192 vs. $M_{partner\ target\ absent}$= 1206 ± 185, right side of Fig. 2) compared to when the agent target was present ($M_{partner\ target\ present}$ = 1955 ± 522 vs. $M_{partner\ target\ absent}$ = 1945 ± 518, left side of Fig. 2). This was indicated by a significant two-way interaction, $F(1, 23) = 19.27$, $p < .001$, $\eta p^2 = .456$, and follow-up t-test indicated which revealed longer responses when the partner target was present than when it was absent in agent target absent trials (ΔM = 72.2 ± 73.5 ms), $t(23) = 4.81$, $p < .001$, which were not significant in agent target present trials (ΔM = 10.2 ± 32.8 ms), $t(23) = 1.52$, $p = .143$. RTs did not differ between the cooperative (M = 1589 ± 551 ms) and the competitive (M = 1603 ± 537 ms) condition, $F(1, 23) = 0.79$, $p = .781$, $\eta p^2 = .003$.

Response accuracies. Accuracies were higher in target present trials (*M* = 99.97 ± 0.14 %) than in target absent trials (*M* = 99.90 ± 0.27 %), *F*(1, 23) = 4.72, *p* = .040, ηp^2 = .170, and were similar for displays that contained the partner target (*M* = 99.94 ± 0.18 %) and the non-relevant distractor (*M* = 99.93 ± 0.25 %), *F*(1, 23) = 0.32, *p* = .575, ηp^2 = .014. Accuracy did not differ between the cooperative (*M* = 99.95 ± 0.17 %) and the competitive (*M* = 99.92 ± 0.25 %) condition, *F*(1, 23) = 0.90, *p* = .354, η_p^2 = .037.

Orientation responses. Deviations of orientation responses did not differ between displays containing the partner target (*M* = 13.20 ± 4.40 °) and non-relevant distractor (*M* = 13.41 ± 4.67 °), *F*(1, 23) = 0.77, *p* = .389, ηp^2 = .032, nor between the cooperative (*M* = 13.49 ± 4.48 °) and the competitive (*M* = 13.11 ± 4.58 °) condition, *F*(1, 23) = 0.95, *p* = .341, ηp^2 = .039.

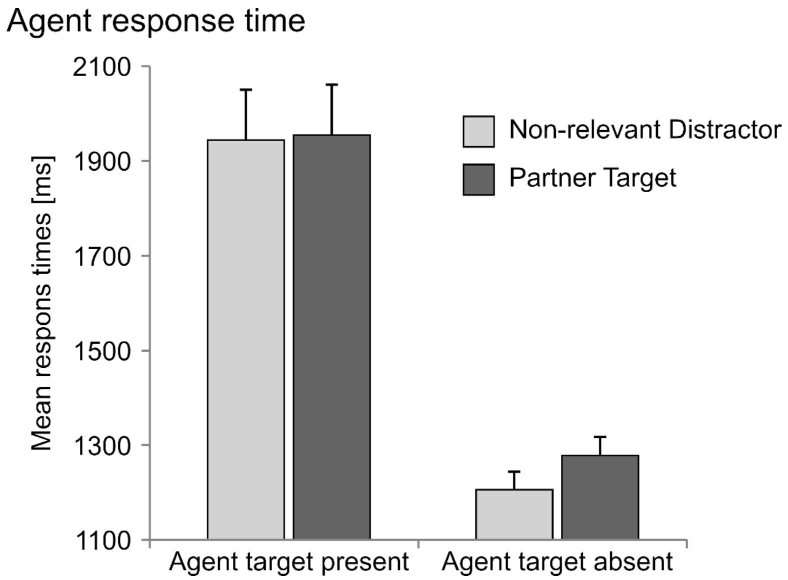


Figure 2. The agent's mean response times. The left two bars show RTs to displays containing the agent target together with either the partner target (dark bar) or a non-relevant color distractor (light bar). The two right bars show RTs to displays containing the partner target together with a non-relevant color distractor (dark bar) or displays containing only two non-relevant color distractors (light bar). Error bars represent standard errors adjusted to within-subject designs (Cousineau, 2005).

Time-Frequency Results

These analyses compare processing of a laterally presented partner target with a laterally presented color distractor of equal salience. As the agent target was shown on the vertical midline, its processing is not reflected in the data. Recent studies have used this kind of lateralization design to unambiguously assign the lateralized alpha-band power to the singleton that appears on the left or right hemifield (Wöstmann, Alavash, & Obleser, 2019; Schneider, Göddertz, Hasse, Hickey, & Wascher, 2019).

Social value: Partner target vs non-relevant distractor (Fig. 3)

To gain a broad view of the attentional effects of social value, we compared lateralized oscillatory power in trials containing a laterally presented partner target to trials containing a laterally presented non-relevant distractor, irrespective of the social context and the stimuli on the vertical meridian. The partner target triggered a negative lateralization in the frequency range of 9 – 14 Hz in the 140 – 300 ms post-stimulus interval (*M* = -0.25 ± 1.72 %; Fig. 3a, left), whereas the non-relevant distractor triggered a positive lateralization (*M* = 1.11 ± 1.85 %) over the same frequency and time range (Fig. 3a, middle), *p* < .05. The cluster of significant differences between the two conditions was detected using the permutation test as is shown in the right panel of Fig. 3a. In trials with the agent target present, the partner target triggered a weak positive lateralization in the frequency range of 6 - 15 Hz in the 80 - 200 ms post-stimulus interval (*M* = 0.26 ± 2.96 %; Fig. 3b, left) whereas the non-relevant distractor triggered a stronger positive lateralization (*M* = 2.05 ± 2.58 %) over the same frequency and time range (Fig. 3b, middle), *p* < .05. The significant cluster of differences between the two conditions is shown in the right panel of Fig. 3b. In trials with the agent target absent, the lateral partner target induced a negative lateralization in the frequency range of 10 - 12 Hz in the 200 - 280 ms post-stimulus interval (*M* = -1.54 ± 4.16 %, Fig. 3c, left), whereas the lateral non-relevant distractor induced a positive lateralization (*M* = 0.75 ± 2.92 %) over the same frequency and time range (Fig. 3c, middle), *p* < .05. This significant cluster of differences between the two conditions is shown in the right panel of Fig. 3c.

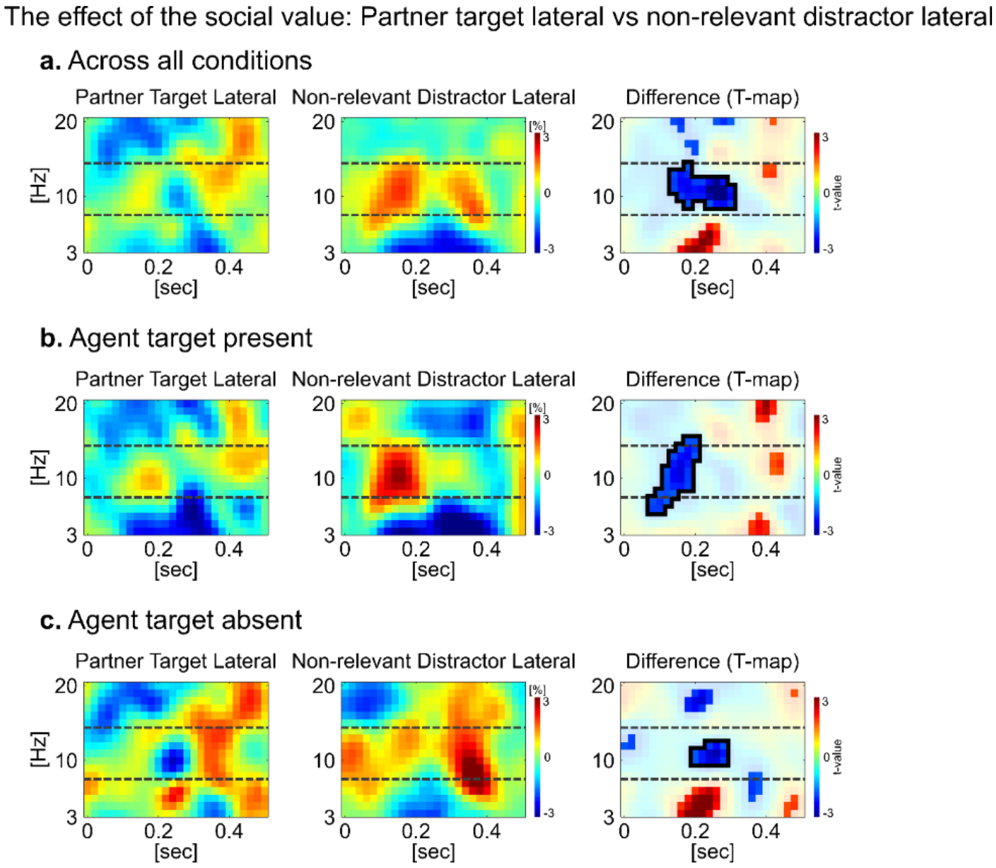


Figure 3. The effect of the social value: Lateralization indices across all conditions **(a)**, when the agent target was present **(b)** and when it was absent **(c)**. The left and middle columns represent averaged lateralized EEG power at posterior-occipital electrodes for a laterally presented partner target (left panels) and a non-relevant color distractor (middle panels). The right columns depict t-values from a cluster-based permutation test comparing lateralization indices. For illustration purposes, the opacity of the non-significant bins ($p > .05$) in T-maps was reduced by 80% and significant clusters of interest were marked by thick black borders. Dashed lines in each panel represent the common range of alpha-band (8 – 14 Hz).

Social context: Cooperative vs competitive task condition (Fig. 4)

To evaluate the impact of social context, we contrasted time-frequency power in the cooperative and the competitive condition.

Lateral Partner Target Trials (Fig. 4a). In the cooperative condition, the partner target induced a negative lateralization in theta/alpha band (4 - 14 Hz) in the 300 - 400 ms post-stimulus interval ($M = -0.76 \pm 3.29$ %; Fig. 4a, left), whereas in the competitive condition it induced a positive lateralization ($M = 1.77 \pm 3.16$ %) over the same frequency and time range (Fig. 4a, middle), $p < .05$. This significant cluster of differences between the two conditions is shown in the right panel of Fig. 4a.

Lateral Non-relevant Distractor Trials (Fig. 4b). When the non-relevant distractor was laterally presented, the permutation test didn't show any cluster of significant differences between cooperative and competitive conditions in the range of alpha band (Fig. 4b, right). As it can be seen in the left and middle panels of Fig. 4b, this was because lateral presentations of the non-relevant distractor triggered positive lateralization of alpha-band power in both the cooperative and competitive conditions.

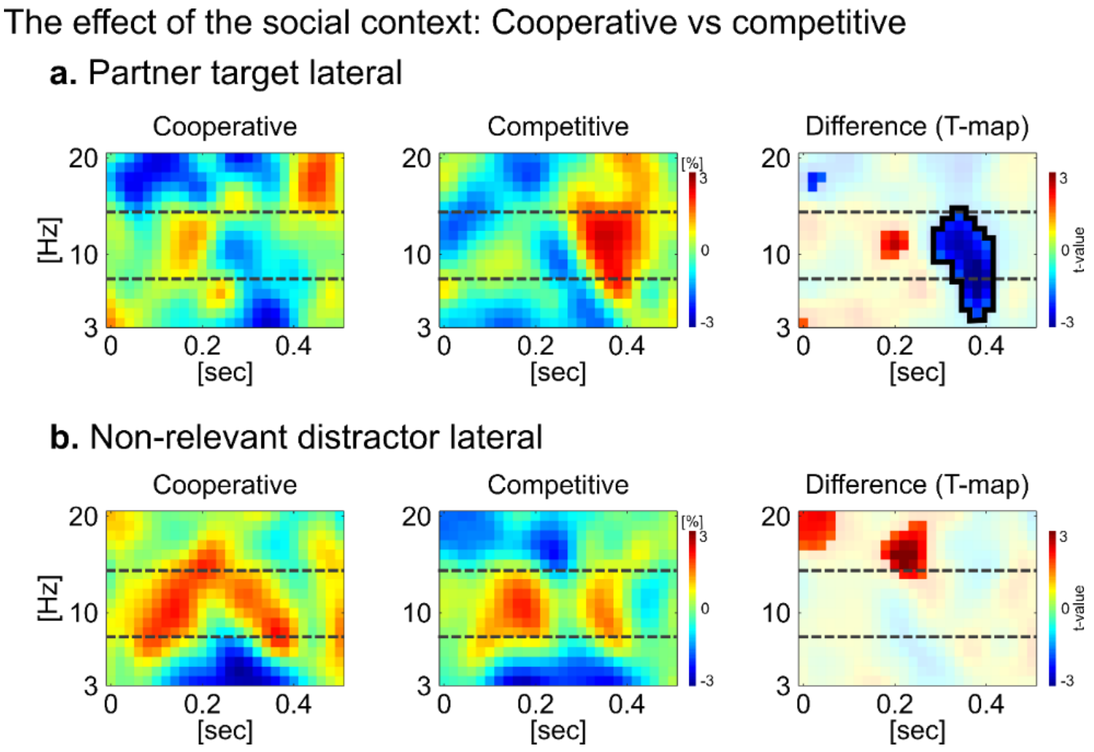


Figure 4. Social context (cooperative vs. competitive condition): Lateralization indices for a laterally presented partner target **(a)** and non-relevant color distractor **(b)** in cooperative (left panels) and competitive (middle panels) conditions. The right columns depict t-values from cluster-based permutation tests comparing lateralization indices between cooperative and competitive conditions. For illustration purposes, the opacity of the non-significant bins (*p* > .05) in T-maps was reduced by 80% and significant clusters of interest were marked by thick black borders. Dashed lines in each panel represent the common range of alpha-band (8 – 14 Hz).

Rating Results

Participants rated the competitive task as more competitive (*M* = 3.44 ± 1.17) than the cooperative task (*M* = 1.63 ± 1.00), *t*(47) = 8.39, *p* < .001. Competition was rated as more unpleasant (*M* = 2.50 ± 1.25) than cooperation (*M* = 1.38 ± 1.27), *t*(47) = 5.16, *p* < .001. The competitive task was rated as more difficult (*M* = 2.75 ± 1.12) than the cooperative task (*M* = 2.58 ± 1.38), *t*(47) = -1.02, *p* = .315. Participants reported that it was similarly difficult to detect the target while competing (*M* = 1.15 ± 1.17) and while cooperating (*M* = 1.48 ± 1.58), *t*(47) = 1.66, *p* = .103. However, participants reported that they detected the partner target more often in the cooperative condition (*M* = 3.96 ± 1.69) than in the competitive condition (*M* = 3.29 ± 2.00), *t*(47) = 2.58, *p* = .013.

Discussion

In this study we examined to what extent a partner target captures visual attention in a joint action task, and whether such a partner target is processed differently when compared to a distractor of equal salience. Pairs of participants sitting side-by-side performed a joint version of the additional singleton paradigm, in which they searched for colored targets and reported their orientation in cooperative and competitive settings while one participant's (the agent's) EEG was recorded. Agent and partner were each assigned one of four colored stimuli as their target. To the agent, the partner target and the non-target distractors of equal luminance were task-irrelevant stimuli. The best strategy for successful performance would therefore have been to completely ignore any non-target stimulus. However, previous studies have shown that agents tend to process a partner target in a functionally similar way as their own in a joint action setting (Sebanz et al., 2003). We therefore expected to see an impact of the partner target on the agent's target selection and a stronger need for distractor suppression in search displays with the partner target present. This should be reflected in differences in behavioral performance and in parieto-occipital alpha-band oscillations when performance in trials with a partner target is compared to performance in trials with a similarly salient, non-relevant color distractor.

Our results showed that the presence of the partner target slowed down the agent's performance, an effect that was more pronounced when the agent target was absent than when it was present. Results from a time-frequency analysis showed a generally negative alpha-band lateralization triggered by the partner target, and a positive alpha-band lateralization elicited by the non-target distractor. Interestingly, the partner target elicited a negative alpha-band lateralization in the cooperative condition, but the same stimulus elicited a positive alpha-band lateralization in the competitive condition.

Presentation of the Partner Target Slows Down Responses

Behavioral results showed that agents took longer to respond in trials with the partner target compared to trials with a non-relevant distractor. Importantly, this RT increase was the strongest when the agent target was absent. When the agent target was absent and the partner target was present, the agent would click on the “No target” button while the partner would report the orientation of their target, that is, participants performed responses of different complexities. When neither target was present, both participants had to click on their respective “No target” button, that is, they performed the same response. Slower responses with different responses might indicate that the agent was aware of the partner’s required action, which interfered with their own response. This interpretation fits well with the action co-representation account (Sebanz et al., 2003). The action co-representation account explains the joint Simon effect as resulting from the interference between the agent’s representation of their own action and the co-representation of the partner’s action (Sebanz et al., 2003, 2006; Tsai et al., 2006; Freundlieb et al., 2017). In our study, presenting the partner target might have activated an incongruent response which interfered with the agent’s own response and prolonged RTs (Atmaca et al., 2011; Saunders et al., 2019).

Our behavioral findings can also be described by the referential coding account (Dolk et al., 2013; 2014). The referential coding account suggests that agents code their action relative to salient events, which might be the partner’s presence in the experimental chamber when participants perform a task alongside a partner. The partner’s presence might lead to a spatial coding of responses dependent on their placement along the horizontal axis. If the response-relevant stimuli are placed on the horizontal dimension (left or right of fixation) as well, responses are slower when stimulus and response coding (being left or right to the partner) are incongruent. Importantly, this effect also appears when the salient event is an inanimate object (e.g., a “waving cat” statue) and not a human partner (Dolk et al., 2013, 2014; Lien et al., 2016). Interestingly, not only the spatial coding, but also coding on other stimulus dimensions can induce a conflict. For example, Sellaro, Dolk, Colzato, Liepelt, & Hommel (2015) used a nonspatial joint Simon task where participants had to wear either red or green gloves while being asked to respond to their assigned shape target (circle vs triangle) by pressing one of two response buttons that had the same color as the gloves. The stimuli were centrally presented and appeared randomly in red or green. The results showed a nonspatial joint Simon effect indicating that participants coded the stimulus color in order to perform better response discrimination although color was response-irrelevant. In our study, participants had to search for a colored Gabor stimulus (their target) and report its orientation. Although color was not associated with a response, the presence of the partner might have initiated a coding of partner’s color features as relevant. As a consequence, the agent’s performance deteriorated when the partner target was present.

The Partner Target is not Just Processed as a Non-relevant Distractor

One important aim of the present study was to investigate how agents deploy their attention when performing a search task alongside a partner. As our behavioral results showed, the agents responded slower when a partner target was present compared to when the partner target was absent and a non-relevant distractor was presented in its place. This result indicates that handling a partner target was more costly than handling a non-relevant distractor. Crucially, the partner target and the non-relevant distractor were of equal visual salience, hence the slower responses in the presence of the partner target cannot be attributed to differences in bottom-up processing and differences on the salience map (Itti & Koch, 2000). Instead, the differential processing likely results from a higher weight assigned to the color corresponding to the partner target on the priority map (Fecteau & Munoz, 2006, Awh et al., 2012; Theeuwes, 2018). A higher weight of a socially relevant target has resulted in a higher degree of attention deployed to the partner target, drawing attention away from the target assigned to the agent.

To investigate neurophysiological correlates of the attentional processes underlying the processing of the partner target compared to the non-relevant distractor, EEG data were analyzed. A growing body of literature has suggested a substantial role of EEG alpha-band oscillations in selective spatial attention (Klimesch 2012; van Diepen, Miller, Mazaheri, & Geng, 2016; Foster & Awh, 2019; Schneider, Herbst, Klatt, & Wöstmann, 2021). Attending to an item has been indexed by a decrease in posterior alpha-band power over the hemifield contralateral to the item location (Bacigalupo & Luck, 2019; Thut, Nietzel, Brandt, & Pascual-Leone, 2006), and has been associated with increased attention deployment to a task-relevant stimulus (Bacigalupo & Luck, 2019; Foster & Awh, 2019; van Diepen et al., 2016; Thut et al., 2006). Another line of research suggests a direct link between alpha–band oscillations and excitability of the visual cortex (Romei, Gross, Thut, 2010; Samaha, Gosseries, & Postle, 2017; van Diepen, Foxe, & Mazaheri, 2019). Decreased pre-stimulus alpha-band power facilitates performance in near-threshold discrimination tasks by increasing participant’s confidence in target discrimination (Samaha et al., 2017). Moreover, the gating by inhibition framework suggests that increased alpha-band power enhances visual spatial attention by suppressing unattended locations (Jensen & Mazaheri, 2010; Händel, Haarmeier, & Jensen, 2011; Wöstmann et al., 2019; Bengson, Liub, Khodayari, & Mangun, 2020). In a recent study, van Zoest, Huber-Huber, Weaver, & Hickey (2021) suggested compelling evidence on the role of pre-stimulus alpha-band power in distractor suppression. In their study, when location or feature of the distractor was cued, an increased posterior alpha-band power in the cue-stimulus interval was observed. Subsequently, this increased alpha-band power was associated with reduced amplitude of post-stimulus distractor positivity, a neurophysiological marker of distractor suppression (Hickey, Di Lollo, & McDonald, 2009). Van Zoest et al. (2021) concluded that distractor suppression, via increased pre-stimulus alpha-band power has a direct consequence in reducing the need for stimulus-triggered distractor suppression.

As expected, the partner target triggered a negative lateralization of alpha-band power in the present study. This finding again points to the higher value the partner target was assigned. A negative lateralization of alpha band indicates attending to or selection of the stimulus in a hemifield (Bacigalupo & Luck, 2019; Thut et al., 2006). As no other color stimulus was laterally presented when the partner target appeared in a hemifield, the negative lateralization of alpha band was solely triggered by the partner target. The negative lateralization of alpha band suggests that the agents attended to the partner target, although it was not their target. This attendance to the partner target has a direct behavioral consequence as participants were slower when the partner target was present.

In contrast to the partner target, the non-relevant distractor triggered a positive lateralization of alpha-band power and this was the case in both types of social contexts. The non-relevant distractor was not instrumental for the agent to perform the task, and neither had any social value. Therefore, the best strategy would be to either suppress or ignore this stimulus. Previous studies have shown that a distractor that is more salient than the target captures the observer's attention (stimulus-driven selection account; Theeuwes, 2010) or triggers an attend-to-me signal that can, under some circumstances, be actively suppressed (signal-suppression account; Sawaki & Luck, 2010; Gaspelin & Luck, 2018; see also Luck et al., 2021, for an elaborate discussion). In either case, the salient distractor needs to be suppressed to achieve a good task performance. Crucially, the color stimuli in the present study were of equal salience, suggesting an equal potential for automatic bottom-up attentional capture or for subsequent distractor suppression. The positive lateralization of alpha-band power in response to the non-relevant distractor suggests a pronounced suppression of this stimulus. However, agents did not suppress the partner target to a similar extent, and in fact, the negative lateralization of alpha-band power in response to it suggests that it even captured attention. The partner target thus not only tends to capture attention due to its high social value, but it is also difficult to successfully suppress.

Our finding of a negative alpha-band lateralization triggered by the partner target is consistent with other recent studies reporting alpha-band modulations when single and joint attention conditions were compared. For instance, Lachat et al. (2012) asked participants to sit face-to-face and direct their eye gaze towards the same (joint attention) or different (single attention) targets. As their results showed, directing gaze toward the same target triggered faster saccadic response time and also a reduced posterior alpha-band power compared to when participants attended different targets. Lachat and colleagues interpreted these findings by referring to attentional suppression (see Worden et al., 2000; Jensen & Mazaheri, 2010; Clayton, Yeung, & Kadosh, 2018): In the single attention condition, participants had to suppress any attentional deployment to the partner or the partner target, and had to focus their attention to their own targets, resulting in increased alpha-band power. In the joint condition, however, suppression was not needed, as participants had to align their attention and attend the same target. Our findings extend the findings from Lachat et al. (2012) in two points: first, Lachat et al. (2012) had participants overtly attended their targets, whereas our study provides evidence for involvement of covert attention in joint action tasks. Second, our findings reveal that participants who share a task also attend to their partner's target when the partners have to search for and respond to different targets. This shows that participants attend to the partner target also when they neither directly share the target nor the task.

Social Context Impacts Attentional Deployment to the Partner Target

The second aim of the study was to examine the impact of the social context on behavior and on the underlying neural processes, as reflected in oscillatory brain activity. Cooperative and competitive social contexts have previously been shown to impact the behavior of jointly acting partners differently. While cooperative conditions tend to increase the impact of the partner task on the agent's response, competitive conditions reduce this effect (Hommel et al., 2009; Ruissen & de Bruijn, 2016; Mendl et al., 2018; but see Ruys & Aarts; 2010). For instance, the Simon effect is larger when participants share a Simon task cooperatively than when the task is shared competitively (Hommel et al., 2009). However, these findings are mixed and more electrophysiological evidence is needed to elucidate the effect of the social context on the partner's task co-representation by the agent. To this end, lateralized oscillatory power in the cooperation and competition condition was analyzed separately and were compared.

In the cooperative condition, the laterally presented partner target elicited a negative lateralization of alpha-band power, while a positive lateralization of alpha-band power was seen in the competitive condition. These findings can be interpreted as indicating that the agent deployed attention to the partner target in the cooperative context, but strived to suppress the partner target in the competitive condition. This interpretation is consistent with the previous findings which have shown that sharing a task in a cooperative relationship increases the impact of the partner target, as indicated by a larger joint Simon effect in a cooperative than in the competitive joint action context (Hommel et al., 2009; Ruissen & de Bruijn, 2016; Mendl et al., 2018). In a study by Ruissen & de Bruijn (2016), the cooperative and competitive relationships between the joint action partners were induced by an initial (Tetris) game before participants were asked to perform a joint Simon task in a neutral social context. The results showed a larger joint Simon effect in the cooperative compared to the competitive condition. As Ruissen & de Bruijn speculated, when the agents compete against their partners, the agents disengage from the partner and increase the attentional focus on their own task to achieve better performance. Our study provides electrophysiological evidence for this interpretation of Ruissen & de Bruijns' behavioral findings. Our results show that the agents tended to attend to the partner target in the cooperative condition and suppress it in the competitive condition to increase the attentional focus on their own target to achieve a better task performance. This suppression of the partner target is reflected in a positive lateralization of alpha-band power contralateral to the location of the partner target. In the cooperative condition, in contrast, the agents tended to attended to the partner target in a similar way as to their own target (Sebanz et al., 2003) which is reflected in a negative lateralization of alpha-band power.

Self-other Integration or Segregation Depends on the Task and Social Context

As pointed out above, competition induces segregation of the own action and the partner's action representation to achieve better performance while cooperation induces integration of both action representations (de Bruijn et al., 2008; Hommel et al., 2009; Novembre, Sammler, & Keller, 2016; Ruissen & de Bruijn, 2016). Our results provide further neurophysiological evidence for this account: We showed that the partner target elicited a positive lateralization of alpha-band power in the competitive condition and a negative lateralization of alpha-band power in the cooperative condition. Our interpretation is that, in the competitive condition, the agents segregate their own action from the partner's action representation by suppressing the partner target, reflected in a positive lateralization of alpha-band power. In the cooperative condition, however, the agents integrate the partner's action with their own action, because the partner's performance contributes to the outcome of the task reflected in negative alpha-band power lateralization.

Conclusion

The present findings add to a growing body of literature reporting attention deployment to the partner target in joint action depending on the social context. As the behavioral results showed, the co-representation of the partner target interfered with the agent's own action and this interference resulted in reduced behavioral performance. The neurophysiological results suggested that the co-representation of the partner target and task is reflected in neural activity in the agent's visual cortex which is different from neural activities observed in the same cortical regions when triggered by a non-relevant distractor, although they both were of equal salience and task-irrelevant for the agent. Furthermore, attention deployment to the partner target depended on the social context: Participants attended to the partner target in a cooperative but rather suppressed it in a competitive social context. In brief, our findings suggest that agents can tune their attention to information relevant to a co-acting partner, and weight information differently depending on the task and social context.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

References

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology*, *59*(4), e13987. https://doi.org/10.1111/psyp.13987

Atmaca, S., Sebanz, N., & Knoblich, G. (2011). The joint flanker effect: sharing tasks with real and imagined co-actors. *Experimental Brain Research*, *211*(3-4), 371-385. https://doi.org/10.1007/s00221-011-2709-9

Bacigalupo, F., & Luck, S. J. (2019). Lateralized suppression of alpha-band EEG activity as a mechanism of target processing. *The Journal of Neuroscience*, *39*(5), 900–917. https://doi.org/10.1523/JNEUROSCI.0183-18.2018

Böckler, A., Knoblich, G., & Sebanz, N. (2012). Effects of a coactor's focus of attention on task performance. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(6), 1404. https://doi.org/10.1037/a0027523

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *The European Journal of Neuroscience*, *48*(7), 2498–2508. https://doi.org/10.1111/ejn.13747

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson’s method. *Tutorials in Quantitative Methods for Psychology*, *1*(1), 42-45. https://doi.org/10.20982/tqmp.01.1.p042

Colzato, L. S., De Bruijn, E., & Hommel, B. (2012). Up to “me” or up to “us”? The impact of self-construal priming on cognitive self-other integration. *Frontiers in Psychology*, *3*, 341. https://doi.org/10.3389/fpsyg.2012.00341

de Bruijn, E. R., Miedl, S. F., & Bekkering, H. (2008). Fast responders have blinders on: ERP correlates of response inhibition in competition. *Cortex*, *44*(5), 580-586. https://doi.org/10.1016/j.cortex.2007.09.003

Dittrich, K., Rothe, A., & Klauer, K. C. (2012). Increased spatial salience in the social Simon task: A response-coding account of spatial compatibility effects. *Attention, Perception & Psychophysics*, *74*(5), 911–929. https://doi.org/10.3758/s13414-012-0304-1

Dolk, T., Hommel, B., Colzato, L. S., Schütz-Bosbach, S., Prinz, W., & Liepelt, R. (2011). How "social" is the social Simon effect? *Frontiers in Psychology*, *2*, 84. https://doi.org/10.3389/fpsyg.2011.00084

Dolk, T., Hommel, B., Colzato, L. S., Schütz-Bosbach, S., Prinz, W., & Liepelt, R. (2014). The joint Simon effect: A review and theoretical integration. *Frontiers in Psychology*, *5*, 974. https://doi.org/10.3389/fpsyg.2014.00974

Dolk, T., Hommel, B., Prinz, W., & Liepelt, R. (2013). The (not so) social Simon effect: A referential coding account. *Journal of Experimental Psychology. Human Perception and Performance*, *39*(5), 1248–1260. https://doi.org/10.1037/a0031031

Fecteau, J. H., & Munoz, D. P. (2006). Salience, relevance, and firing: A priority map for target selection. *Trends in Cognitive Sciences*, *10*(8), 382-390. https://doi.org/10.1016/j.tics.2006.06.011

Fitzpatrick, P., Mitchell, T., Schmidt, R. C., Kennedy, D., & Frazier, J. A. (2019). Alpha band signatures of social synchrony. *Neuroscience Letters*, *699*, 24–30. https://doi.org/10.1016/j.neulet.2019.01.037

Foster, J. J., & Awh, E. (2019). The role of alpha oscillations in spatial attention: limited evidence for a suppression account. *Current Opinion in Psychology*, *29*, 34–40. https://doi.org/10.1016/j.copsyc.2018.11.001

Freundlieb, M., Sebanz, N., & Kovács, Á. M. (2017). Out of your sight, out of my mind: Knowledge about another person's visual access modulates spontaneous visuospatial perspective-taking. *Journal of Experimental Psychology. Human Perception and Performance*, *43*(6), 1065–1072. https://doi.org/10.1037/xhp0000379

Gaspelin, N., & Luck, S. J. (2018). The role of inhibition in avoiding distraction by salient stimuli. *Trends in Cognitive Sciences*, *22*(1), 79–92. https://doi.org/10.1016/j.tics.2017.11.001

Hauswald, A., Tucciarelli, R., & Lingnau, A. (2018). MEG adaptation reveals action representations in posterior occipitotemporal regions. *Cortex, 103*, 266–276. https://doi.org/10.1016/j.cortex.2018.03.016

Händel, B. F., Haarmeier, T., & Jensen, O. (2011). Alpha oscillations correlate with the successful inhibition of unattended stimuli. *Journal of Cognitive Neuroscience, 23*(9), 2494–2502. https://doi.org/10.1162/jocn.2010.21557

Hommel, B., Colzato, L. S., & van den Wildenberg, W. P. (2009). How social are task representations? *Psychological Science*, *20*(7), 794–798. https://doi.org/10.1111/j.1467-9280.2009.02367.x

Hommel, B., Müsseler, J., Aschersleben, G., & Prinz, W. (2001). The Theory of Event Coding (TEC): A framework for perception and action planning. *The Behavioral and Brain Sciences, 24*(5), 849–937. https://doi.org/10.1017/s0140525x01000103

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience, 4*, 186. https://doi.org/10.3389/fnhum.2010.00186

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606-617. https://doi.org/10.1016/j.tics.2012.10.007

Kourtis, D., Knoblich, G., Woźniak, M., & Sebanz, N. (2014). Attention allocation and task representation during joint action planning. *Journal of Cognitive Neuroscience*, *26*(10), 2275–2286. https://doi.org/10.1162/jocn_a_00634

Lachat, F., Hugueville, L., Lemaréchal, J. D., Conty, L., & George, N. (2012). Oscillatory Brain Correlates of Live Joint Attention: A Dual-EEG Study. *Frontiers in Human Neuroscience, 6*, 156. https://doi.org/10.3389/fnhum.2012.00156

Lien, M. C., Pedersen, L., & Proctor, R. W. (2016). Stimulus-response correspondence in go-nogo and choice tasks: Are reactions altered by the presence of an irrelevant salient object? *Psychological Research, 80*(6), 912–934. https://doi.org/10.1007/s00426-015-0699-0

Luck, S. J., Gaspelin, N., Folk, C. L., Remington, R. W., & Theeuwes, J. (2021). Progress toward resolving the attentional capture debate. *Visual Cognition, 29*(1), 1–21. https://doi.org/10.1080/13506285.2020.1848949

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods, 164*(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Mathôt, S. (2022, March 26). *Online Gabor-patch generator*. Cogsci. https://www.cogsci.nl/gabor-generator

Mendl, J., Fröber, K., & Dolk, T. (2018). Are you keeping an eye on me? The influence of competition and cooperation on joint Simon task performance. *Frontiers in Psychology*, *9*, 1361. https://doi.org/10.3389/fpsyg.2018.01361

Michael, J., Sebanz, N., & Knoblich, G. (2016). Observing joint action: Coordination creates commitment. *Cognition, 157*, 106-113. https://doi.org/10.1016/j.cognition.2016.08.024

Naeem, M., Prasad, G., Watson, D. R., & Kelso, J. A. (2012). Electrophysiological signatures of intentional social coordination in the 10-12 Hz range. *NeuroImage*, *59*(2), 1795–1803. https://doi.org/10.1016/j.neuroimage.2011.08.010

Novembre, G., Sammler, D., & Keller, P. E. (2016). Neural alpha oscillations index the balance between self-other integration and segregation in real-time joint action. *Neuropsychologia*, *89*, 414-425. https://doi.org/10.1016/j.neuropsychologia.2016.07.027

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, *2011*, 156869. https://doi.org/10.1155/2011/156869

Prinz, W. (1997). Perception and action planning. *European Journal of Cognitive Psychology*, *9*(2), 129-154. https://doi.org/10.1080/713752551

Romei, V., Gross, J., & Thut, G. (2010). On the role of prestimulus alpha rhythms over occipito-parietal areas in visual input regulation: Correlation or causation? *The Journal of Neuroscience*, *30*(25), 8692–8697. https://doi.org/10.1523/JNEUROSCI.0160-10.2010

Ruissen, M. I., & de Bruijn, E. R. (2016). Competitive game play attenuates self-other integration during joint task performance. *Frontiers in Psychology*, *7*, 274. https://doi.org/10.3389/fpsyg.2016.00274

Ruys, K. I., & Aarts, H. (2010). When competition merges people's behavior: Interdependency activates shared action representations. *Journal of Experimental Social Psychology*, *46*(6), 1130-1133. https://doi.org/10.1016/j.jesp.2010.05.016

Saunders, D. R., Melcher, D., & van Zoest, W. (2019). No evidence of task co-representation in a joint Stroop task. *Psychological Research*, *83*(5), 852–862. https://doi.org/10.1007/s00426-017-0909-z

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, Perception & Psychophysics*, *72*(6), 1455–1470. https://doi.org/10.3758/APP.72.6.1455

Schneider, D., Göddertz, A., Haase, H., Hickey, C., & Wascher, E. (2019). Hemispheric asymmetries in EEG alpha oscillations indicate active inhibition during attentional orienting within working memory. *Behavioural Brain Research*, *359*, 38–46. https://doi.org/10.1016/j.bbr.2018.10.020

Schneider, D., Herbst, S. K., Klatt, L. I., & Wöstmann, M. (2021). Target enhancement or distractor suppression? Functionally distinct alpha oscillations form the basis of attention. *The European Journal of Neuroscience*, 10.1111/ejn.15309. https://doi.org/10.1111/ejn.15309

Sebanz, N., Bekkering, H., & Knoblich, G. (2006). Joint action: Bodies and minds moving together. *Trends in Cognitive Sciences*, *10*(2), 70-76. https://doi.org/10.1016/j.tics.2005.12.009

Sebanz, N., Knoblich, G., & Prinz, W. (2003). Representing others' actions: Just like one's own? *Cognition, 88*(3), B11-B21. https://doi.org/10.1016/S0010-0277(03)00043-X

Sebanz, N., Knoblich, G., Prinz, W., & Wascher, E. (2006). Twin peaks: An ERP study of action planning and control in coacting individuals. *Journal of Cognitive Neuroscience*, *18*(5), 859-870. https://doi.org/10.1162/jocn.2006.18.5.859

Sebanz, N., Rebbechi, D., Knoblich, G., Prinz, W., & Frith, C. D. (2007). Is it really my turn? An event-related fMRI study of task sharing. *Social Neuroscience*, *2*(2), 81-95. https://doi.org/10.1080/17470910701237989

Sellaro, R., Dolk, T., Colzato, L. S., Liepelt, R., & Hommel, B. (2015). Referential coding does not rely on location features: Evidence for a nonspatial joint Simon effect. *Journal of Experimental Psychology. Human Perception and Performance*, *41*(1), 186–195. https://doi.org/10.1037/a0038548

Theeuwes, J. (1992). Perceptual selectivity for color and form. *Perception & Psychophysics*, *51*(6), 599-606. https://doi.org/10.3758/bf03211656

Theeuwes J. (2010). Top-down and bottom-up control of visual selection. *Acta Psychologica*, *135*(2), 77–99. https://doi.org/10.1016/j.actpsy.2010.02.006

Thut, G., Nietzel, A., Brandt, S. A., & Pascual-Leone, A. (2006). α-Band electroencephalographic activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience*, *26*(37), 9494-9502. https://doi.org/10.1523/JNEUROSCI.0875-06.2006

Tsai, C. C., Kuo, W. J., Jing, J. T., Hung, D. L., & Tzeng, O. J. L. (2006). A common coding framework in self–other interaction: evidence from joint action task. *Experimental Brain Research*, *175*(2), 353-362. https://doi.org/10.1007/s00221-006-0557-9

van Diepen, R. M., Miller, L. M., Mazaheri, A., & Geng, J. J. (2016). The Role of Alpha Activity in Spatial and Feature-Based Attention. *eNeuro*, *3*(5), ENEURO.0204-16.2016. https://doi.org/10.1523/ENEURO.0204-16.2016

van Zoest, W., Huber-Huber, C., Weaver, M. D., & Hickey, C. (2021). Strategic distractor suppression improves selective control in human vision. *The Journal of Neuroscience, 41*(33), 7120–7135. https://doi.org/10.1523/JNEUROSCI.0553-21.2021

Wildegger, T., van Ede, F., Woolrich, M., Gillebert, C. R., & Nobre, A. C. (2017). Preparatory α-band oscillations reflect spatial gating independently of predictions regarding target identity. *Journal of Neurophysiology*, *117*(3), 1385–1394. https://doi.org/10.1152/jn.00856.2016

Wöstmann, M., Alavash, M., & Obleser, J. (2019). Alpha oscillations in the human brain implement distractor suppression independent of target selection. *The Journal of Neuroscience, 39*(49), 9797–9805. https://doi.org/10.1523/JNEUROSCI.1954-19.2019

Worden, M. S., Foxe, J. J., Wang, N., & Simpson, G. V. (2000). Anticipatory biasing of visuospatial attention indexed by retinotopically specific alpha-band electroencephalography increases over occipital cortex. *The Journal of Neuroscience*, *20*(6), RC63. https://doi.org/10.1523/JNEUROSCI.20-06-j0002.2000

APPENDIX

Author contributions in percentages

Study I

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology, 59*(4), e13987. https://doi.org/10.1111/psyp.13987

Hossein Abbasi: 70%
Hanna Kadel: 20%
Clayton Hickey: 5%
Anna Schubö: 5%

Study II

Abbasi, H., Henare, D., Kadel, H., & Schubö, A. (2022). Selection history and task predictability determine the precision expectations in attentional control. *Psychophysiology, e14151*. https://doi.org/10.1111/psyp.14151

Hossein Abbasi: 70%
Dion Henare: 10%
Hanna Kadel: 10%
Anna Schubö: 10%

Study III

Meibodi, N., **Abbasi, H.**, Schubö, A., & Endres, D. M. (2021). A model of selection history in visual attention. *In Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 43, No. 43)

Neda Meibodi: 70%
Hossein Abbasi: 10%
Anna Schubö: 10%
Dominik Endres: 10%

Study IV

Abbasi, H., Dötsch, D., & Schubö, A. (submitted). I see what you see: EEG correlates of attentional capture by a partner target in joint action

Hossein Abbasi: 70%
Dominik Dötsch: 20%
Anna Schubö: 10%

Hossein Abbasi

Prof. Dr. Anna Schubö

Zusammenfassung

Jeden Tag führen wir viele Aufgaben aus, entweder allein oder gemeinsam mit anderen Menschen (joint action), bei denen wir unsere Aufmerksamkeit auf unsere Ziele richten und eine Reihe von Distraktoren ausblenden müssen, die sonst unsere Aufgabenleistung beeinträchtigen. Es gibt mehrere Faktoren, die die Aufmerksamkeit für irrelevante Objekte erhöhen können, wodurch es schwieriger wird, sie auszublenden, z. B. die selection history (Awh, Belopolsky, & Theeuwes, 2012). Andererseits erleichtert die Vorhersagbarkeit der Aufgabe die Auswahl des Ziels und die Unterdrückung der Wahrnehmung von Distraktoren durch einen proaktiven Kontrollmechanismus (Braver, 2012), der vor der Stimuluspräsentation einsetzt. Es hat sich jedoch gezeigt, dass Einflüsse aus der selection history die Aufmerksamkeit auf einen Distraktor auch dann noch fesseln, wenn die Teilnehmer die bevorstehende Aufgabe vorhersagen können (Kadel, Feldmann-Wüstefeld, & Schubö, 2017). Andere Faktoren, die die Salienz eines Objekts beeinflussen, insbesondere bei Aufgaben mit gemeinsamen Handlungen, sind der soziale Wert und der soziale Kontext. In früheren Forschungsarbeiten wurde über die Co-Repräsentation eines Targets des Partners durch einen Probanden berichtet (Sebanz, Knoblich, & Prinz, 2003), die im kooperativen Kontext vorhanden und im kompetitiven Kontext nicht vorhanden ist (Hommel, Colzato, & van Den Wildenberg, 2009). Es gibt jedoch noch einige Lücken in der Literatur, die in dieser Dissertation geschlossen werden sollen. Erstens, ist noch nicht ausreichend erforscht, wie proaktive Vorbereitung in Gegenwart der selection history umgesetzt wird. Vor allem fehlt es an Wissen über die Hirnaktivität während der Aufgabenvorbereitung und den Einfluss der selection history auf diese. Zweitens, wurden der Einfluss des sozialen Werts und des sozialen Kontexts auf die Aufmerksamkeit und die zugehörigen neuronalen Grundlagen noch nicht ausreichend untersucht. Diese Zusammenhänge werden in der vorliegenden Dissertation erforscht.

Diese Dissertation gliedert sich in zwei Hauptteile. Im ersten Teil (Studien I - III) ist die zentrale Forschungsfrage, ob und wie die Vorhersagbarkeit der Aufgabe die durch die selection history induzierten Aufmerksamkeitsverzerrungen moduliert. Im zweiten Teil (Studie IV) ist das Hauptziel die Untersuchung des Einflusses des sozialen Wertes und des sozialen Kontextes auf die Ablenkung der Aufmerksamkeit durch Distraktoren. Um eine individuelle selection history zu induzieren, kategorisieren die Teilnehmer im ersten Teil der Dissertation entweder die Farbe des Farbsingletons (Farbgruppe) oder die Form des Formsingletons (Formgruppe) in einer Kategorisierungsaufgabe. Anschließend führen alle Teilnehmer eine Suchaufgabe durch, bei der ein diamantförmiges Target ausgewählt werden muss, während in einigen Fällen gleichzeitig ein roter Kreis präsentiert wird. Entscheidend ist, dass die Aufgaben unterschiedlich gut vorhersagbar waren (Studien I und II): In Studie I ist die Aufgabensequenz entweder vorhersehbar oder unvorhersehbar, während sie in Studie II immer vorhersehbar ist, allerdings mit einem unterschiedlichen Grad an Zuverlässigkeit (gut vorhersehbar vs. schlecht vorhersehbar). Diese Variationen der Vorhersagbarkeit der Aufgabe ermöglichen eine systematische

Untersuchung des Einflusses der proaktiven Vorbereitung auf die Aufmerksamkeitsverzerrungen in der selection history.

Studie I zeigt, dass eine proaktive Vorbereitung erforderlich ist, wenn die bevorstehende Aufgabe vorhersehbar ist. Diese proaktive Vorbereitung spiegelt sich in einer verringerten Leistung des posterioren Alpha-Bandes vor dem Einblenden des Stimulus wider, allerdings nur in vorhersehbaren Sequenzblöcken. Wichtig ist, dass die proaktive Vorbereitung durch die individuelle selection history skaliert wird - die Teilnehmer der Farbgruppe, die beim Wechsel zwischen den Aufgaben eine stärkere Anpassung des Aufgabensets benötigen, profitierten mehr von der Vorhersagbarkeit der Aufgaben und üben eine stärkere proaktive Vorbereitung aus. Folglich müssen diese Teilnehmer keine starke Distraktorunterdrückung nach Stimulusbeginn ausüben. Dies spiegelt sich in der Amplitude der early Pd component (ein Marker für frühe Distraktorunterdrückung) wider, die unabhängig von der Vorhersagbarkeit der Aufgabe gleichbleibt. Die Teilnehmer der Formgruppe müssen jedoch ihre schwächere proaktive Vorbereitung vor Stimulusbeginn durch eine frühe Unterdrückung des Distraktors kompensieren, was sich in einer größeren early Pd Amplitude in vorhersagbaren im Vergleich zu unvorhersagbaren Sequenzblöcken zeigt. Die Ergebnisse von Studie I werden in Studie II weiter erforscht, in welcher die Aufgabensequenz in einer Sitzung konstant und zwischen den Sitzungen unterschiedlich ist. Es zeigt sich, dass eine zunehmende Vorhersagbarkeit nur einen geringen Einfluss auf die proaktive Distraktorunterdrückung in der Formgruppe hat. Dies liegt möglicherweise daran, dass das Wissen über die Targetdimension für eine optimale Aufgabenerfüllung ausreicht und die Vorhersagbarkeit der Aufgabe die Informationen über die Dimensionen von Target und Distraktor für diese Gruppe nicht verändert. Die Teilnehmer der Farbgruppe unterdrücken den Distraktor jedoch stärker, wenn die Vorhersagbarkeit der Aufgabe zuverlässiger ist, was auf die Nutzung einer proaktiven Vorbereitung hindeutet, wenn die Aufgabe dies erfordert.

Die selection history erhöht die Fokussierung der Aufmerksamkeit auf den Distraktor, wenn Eigenschaften dieses Distraktors innerhalb der Dimension schon an der vorherigen Selektion beteiligt waren. Dies zeigt sich in Studie II in der Farbgruppe, in der die Vorhersagbarkeit der Aufgabe weniger zuverlässig ist, durch das Auftreten der N2pc Komponente nach Präsentation des Distraktors. Die proaktive Vorbereitung erleichtert die Unterdrückung des Distraktors durch die Teilnehmer der Farbgruppe, was sich durch eine kleinere N2pc Komponente nach der Distraktor Präsentation und eine größere early Pd Komponente zeigt, für den Fall, dass die Vorhersagbarkeit der Aufgabe zuverlässig ist. Obwohl die Teilnehmer der Farbgruppe einen größeren Nutzen aus der Vorhersagbarkeit der Aufgabe ziehen, bleibt die Target-Selektion durch diese Teilnehmer beeinträchtigt, wenn der Farbdistraktor präsent ist. Diese verminderte Target-Selektion spiegelt sich in größeren Verhaltenskosten (distractor costs) und einem späteren Einsetzen der target N2pc in der Farbgruppe verglichen mit der Formgruppe wider. Diese Ergebnisse zeigen, dass die proaktive Unterdrückung von Distraktoren nicht in der Lage ist, die durch die selection history induzierten Aufmerksamkeitsverzerrungen aufzuheben.

Der Einfluss der selection history auf die Prioritätskarte (priority map) wird in Studie III mit Hilfe eines algorithmischen Modells quantitativ bewertet. Das Modell berechnet für jede Gruppe die Gewichtung von vier verschiedenen Karten (Historie, Farbe, Form und Orientierung). In der Farbgruppe ist das Gewicht der Historiekarte sehr hoch und größer als in der Formgruppe. Dies zeigt, dass die Personen in der Farbgruppe sich mehr auf ihre selection history verlassen, da sie diese zur Erfüllung der Kategorisierungsaufgabe benötigen. Andererseits war das Gewicht der Formkarte in der Formgruppe am höchsten. Dies deutet darauf hin, dass die Teilnehmer der Formgruppe beide Aufgaben bewältigen können, indem sie sich auf die Formunterscheidung verlassen, ohne auf ihre Historie zurückgreifen zu müssen. Wichtig ist, dass die Farbkarte in der Farbgruppe ein größeres Gewicht hat als in der Formgruppe, was die größere Fokussierung der Aufmerksamkeit auf den Distraktor in der Farbgruppe im Vergleich mit der Formgruppe erklärt. Daher kann das Modell quantitative Messwerte für jede Karte liefern und erklären, wie die selection history mit den physikalischen Eigenschaften der Stimuli bei der Lenkung der Aufmerksamkeit in der Prioritätskarte interagiert.

Im zweiten Teil der vorliegenden Dissertation (Studie IV) teilen sich Paare von Teilnehmern eine gemeinsame Aufgabe, entweder kooperativ oder kompetitiv, wobei die Teilnehmer auf ihr eigenes Target (agent target vs. partner target) reagieren müssen. Entscheidend ist, dass in einigen Versuchen ein farbiger Distraktor vorhanden ist, der für keinen der Teilnehmer das Target ist (nicht-relevanter Distraktor). Obwohl sowohl das Target des Partners, als auch der nicht-relevante Distraktor für den Probanden keine Targets sind, erregten sie die Aufmerksamkeit des Probanden auf unterschiedliche Weise. Während das Target des Partners die Aufmerksamkeit des Probanden auf sich zieht, was sich in einer negativen Lateralisierung der parieto-occipitalen Alpha-Band Energie und einer längeren Reaktionszeit zeigt, wird der nicht-relevante Distraktor unterdrückt, was zu einer positiven Lateralisierung der parieto-occipitalen Alpha-Band Energie führt. Wichtig ist, dass die Fokussierung der Aufmerksamkeit auf das Target des Partners vom sozialen Kontext abhängt. Während das Target des Partners die Aufmerksamkeit des Probanden in der kooperativen Bedingung auf sich zieht, was durch eine negative Lateralisierung der parieto-occipitalen Alpha-Band Energie zu sehen ist, wird derselbe Stimulus in der kompetitiven Bedingung unterdrückt und zeigt sich in einer positiven Lateralisierung der parieto-occipitalen Alpha-Band Energie. Dies deutet darauf hin, dass die Teilnehmer ihre Aufmerksamkeit in Abhängigkeit vom sozialen Kontext und der Aufgabe auf das Target des Partners richten.

Zusammenfassend wird in den vier Studien dieser Dissertation der Einfluss verschiedener Faktoren wie Vorerfahrung, Vorhersagbarkeit der Aufgabe, sozialer Wert und sozialer Kontext auf die Ausrichtung der Aufmerksamkeit untersucht. Es zeigt sich, dass frühere Erfahrungen mit einer Merkmalsdimension die Salienz der Stimuli in dieser Dimension erhöhen und damit die Fokussierung der Aufmerksamkeit darauf steigern.

Obwohl eine Erhöhung der Vorhersagbarkeit der Aufgabe die durch die selection history induzierten Aufmerksamkeitsverschiebungen verringert, kann sie den Einfluss der selection history nicht vollständig aufheben. Außerdem wird gezeigt, dass der soziale Wert die Aufmerksamkeit auf die Stimuli verändert. Das Target des Partners zieht die Aufmerksamkeit auf sich, während der nicht-relevante Stimulus, der eine ähnliche Luminanz hat, unterdrückt wird. Es wird außerdem gezeigt, dass die Fokussierung der Aufmerksamkeit durch das Target des Partners eine Funktion des sozialen Kontexts ist. Die vorliegende Dissertation legt daher nahe, dass die Aufmerksamkeitskontrolle flexibel ist, da die Fokussierung der Aufmerksamkeit auf den Distraktor in Abhängigkeit von Faktoren wie der Vorhersagbarkeit der Aufgabe, früheren Erfahrungen, dem sozialen Wert und dem sozialen Kontext variieren kann.

Curriculum Vitae

Page 146 contains personal data. It is therefore not part of the online publication.

Publications

Abbasi H., Dötsch D., & Schubö A. (submitted). I see what my partner sees: EEG correlates for attentional capture by a partner's target in joint action.

Abbasi, H., Henare, D., Kadel, H., & Schubö, A. (2023). Selection history and task predictability determine the precision expectations in attentional control. *Psychophysiology, e14151*. https://doi.org/10.1111/psyp.14151

Abbasi, H., Kadel, H., Hickey, C., & Schubö, A. (2022). Combined influences of strategy and selection history on attentional control. *Psychophysiology, 59*(4), e13987. https://doi.org/10.1111/psyp.13987

Meibodi, N., **Abbasi, H.**, Schubö, A., & Endres, D. (2021, April 27). Distracted by previous reward: Integrating selection history, current task demands and saliency in a computational model. *PsyArXiv*. https://doi.org/10.31234/osf.io/mbe5a

Meibodi, N., **Abbasi, H.**, Schubö, A., & Endres, D. M. (2021). A model of selection history in visual attention. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 43, No. 43). https://escholarship.org/uc/item/3m33h9h7

Conferences and presentations

Abbasi H., Dötsch D., & Schubö A. (2018). Neurophysiological correlates of joint action: EEG correlates for attentional capture by a partner's target in joint action. *International Research Training Group (IRTG) meeting*, Frankfurt, Germany.

Abbasi H., Dötsch D., & Schubö A. (2019). "Neurophysiological correlates of joint action" *OHBM 2019 – Organization for Human Brain Mapping*. Rome, Italy.

Abbasi H., Kadel H., Hickey C., & Schubö A. (2019) "Individual selection history biases visual attention depending on the task preparation". *International Research Training Group (IRTG) meeting*, Grand Bend, Ontario, Canada.

Abbasi H., King C., Schlebusch S., Röder B., Groh J., & Bruns P. (2022). "Eye movement-related eardrum oscillations do not require current visual input". *IMRF 2022 – International Multisensory Research Forum.* Ulm, Germany

Acknowledgements

Completion of this dissertation would not have been possible without the help of many people whom I want to appreciate here.

My biggest and sincerest gratitude goes to my amazing supervisor, Prof. Anna Schubö. Dear Anna, thanks for letting me do my PhD in your group! Thanks for teaching me how to look at questions in the field of visual attention! Thanks for the trust and for encouraging me to get involved in different projects! I could always feel extra energy after our meetings. Discussing our findings and your comments on my writing were always invaluable to me. Thanks for everything!

Thanks to Prof. Dominik Endres for accepting to be the second supervisor of my PhD dissertation and for reading and evaluating my dissertation. Dear Dominik, collaborating with you was the best motivation for me to step into the modeling world and it was indeed very productive. I would like to thank my overseas supervisor, Prof. Gunnar Blohm. Dear Gunnar, thanks for hosting me in your lab for three months! You were always the only person who asked me questions after my IRTG retreat presentations and it meant a lot to me.

I would like to give special thanks to Dr. Clayton Hickey, Dr. Dion Henare, Hanna Kadel, Dominik Dötsch, and Neda Meibodi for our productive collaborations. Dear Hanna and Dominik, I really learned a lot from you and I will never forget your support when I started my PhD. Dear Clayton, you are amazing in the field of attention. Your professionalism and kindness were so obvious to me from our first meeting, and I learned a lot from you. Dear Neda, our scientific meetings were never empty of fun. It was great to work with you as a “modeling” person and as a friend.

A very big thanks goes to the current and past Schubö’s lab members, Phillip Berg, Nils Bergmann, Jan Tünnermann, Yunyun Mu, Aylin Hanne, Kevin Hartung, Geun Hyun Kim, and Anna Heuer. It was so great to work with you. Our lunches together were always so much fun for me. This was also a great chance for me to be part of the IRTG program. I would like to thank all IRTG members for our nice meetings, retreats, discussions, and all the fun! I also want to thank all the research assistants who collected data for my projects and all the participants involved in my experiments.

I would like to thank my lovely brother, Dr. Omid Abbasi. Dear Omid, no one can ignore all the support I have received from you from the first moment of my life that I remember. You have not only been a brother to me, but a friend, coach, and teacher. I am so proud of having you around. I also would like to thank Dr. Constanze Schmitt for all her support in the last four years of my life. Constanze has always been encouraging me in my work and she always helped me whenever I was exhausted, stressed, or disappointed.

I would also like to thank Dr. Patrick Bruns and Prof. Brigitte Röder for letting me work with them for the past year. Dear Patrick, thanks for being so generous to me, and thanks for all your support when I was writing this dissertation! Thanks to all my amazing friends which I had the chance to know during my PhD, Dr. Alejandro Gloriani, Dr. Adela Park, Dr. Christian Wolf, Byung-Woo Hwang, Zahra Khosrowtaj, Alireza Hatami, and Janis Kan. Especially, I would like to thank Dr. Adela Park and Dr. Constanze Schmitt for reading and commenting on this dissertation. I also thank family Schmitt for all the support during my PhD. I was always so refreshed and full of energy after meeting them.

Last, but not least, I would like to thank my lovely family in Iran. They have always been the source of love, energy, happiness, motivation, and strength for me. I am so grateful for having such a supportive family. I would like to dedicate this work to those who spent the last four decades of their life to shape me into who I am now, my parents.

Erklärung

Hiermit versichere ich, die vorliegende Dissertation
“Neural underpinnings of preparatory processes: The roles of prediction, previous experience and social context in attentional control”
selbstständig, ohne fremde, unerlaubte Hilfe und mit keinen anderen als den ausdrücklich bezeichneten Quellen und Hilfsmitteln verfasst zu haben. Alle vollständigen oder sinngemäßen Zitate sind als solche gekennzeichnet. Die Dissertation wurde in der jetzigen oder einer ähnlichen Form bei keiner anderen Hochschule eingereicht und diente bislang keinen anderen Prüfungszwecken.

____

(Hossein Abbasi)

Marburg, September 2022