How the visual environment shapes attention: The role of context in attention guidance

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SUMMARY

In our environment, visual stimuli typically appear within the context of other stimuli, which are usually not arranged randomly but follow regularities. These regularities can be very useful for the visual system to overcome the problem of limited encoding capacity by guiding attention to stimuli which are relevant for behavior. There is growing evidence that observers use repeated contexts for guiding attention in visual search, and there is evidence that observers adapt to dynamical changes in their visual environment. However, contexts in our natural environment often come with features predicting reward, and little is known about the influence of such reward-predicting contexts on attention guidance. In addition, it is unclear how observers adapt their behavior to context features that are not relevant for the task, and little is known about individual differences in the effects of contexts. These research gaps are addressed in the present dissertation. In five studies, the present dissertation investigates how different types of contextual regularities are integrated into behavior and how these regularities guide visual attention.

The main part of this dissertation (Studies I-III) focuses on visual contexts that do not change over time and are encountered repeatedly ("repeated contexts"). To this end, Studies I-III used the contextual cueing paradigm (Chun & Jiang, 1998), a visual search paradigm in which participants have to locate a target among a context configuration of distractors. In Studies I and II, half of these distractor configurations repeated throughout the experiments, whereas the other half were generated newly for each trial. In both studies, it was observed that participants responded faster in repeated compared to novel contexts. This effect developed in the course of each experiment and is known as *contextual cueing (CC) effect*.

Participants not only responded faster but they also moved their eyes more efficiently to the target in repeated (compared to novel) contexts. This indicates that attention guidance was facilitated by the repeated context configurations and that participants used the contexts for finding the target. Study III showed that participants could not only use contexts that repeated entirely, but also contexts in which only a very limited amount of contextual information was repeated. With only three distractors repeating, participants basically showed similar CC effects as observed for entirely repeated contexts. This surprising result suggests that even a small amount of repeating contextual information is sufficient for guiding attention to the target.

As a crucial novelty compared to previous studies, Studies I-III investigated the role of context features signaling motivational value by associating reward. In Study I, half of the context items were presented in a task-irrelevant color, which signaled either a low, medium, or a high reward. Participants showed an increased CC effect for contexts with a color signaling high reward. The increased CC effect was caused by reduced response times in high reward

repeated contexts, while response times in novel contexts were unaffected by reward. In addition, participants were also more efficient in moving their eyes to the target in high compared to low or medium reward repeated contexts, which indicates that reward boosted contextual cueing by facilitating attention guidance to the target.

Study II replicated the increased CC effect for contexts predicting a high reward. In Study II, however, reward was associated with a task-relevant context feature, namely, the predominant orientation of the distractor items. In addition, Study II examined the emergence and persistence of the reward effect more closely. The results showed that reward persistently increased contextual cueing rather than leading to an earlier emerging but asymptotically similar effect, as was assumed in previous studies (cf. Tseng & Lleras, 2013). Study III examined whether reward-predicting colors influenced task performance in a similar manner in contexts that repeated entirely and in contexts that repeated only in part. Surprisingly, reward had no effect on contextual cueing in Study III, neither in partially nor in entirely repeated contexts. There was evidence that most participants did not learn to associate color with reward magnitude which could explain why reward had no effect. Hence, the missing reward effect in Study III does not contradict the results of Studies I and II. Taken together, the first part of this dissertation demonstrates that contexts are prioritized in context configuration learning when they predict a high reward. In repeated contexts that predict high reward, attention is guided more efficiently to the target, a benefit which persists even after many context repetitions.

The second part of this dissertation (Study IV) studies how observers use contexts that change dynamically in a predictable sequence. Using the adaptive choice visual search paradigm (ACVS, Irons & Leber, 2016), Study IV demonstrated that observers adapt their choice between two targets to a predictable color change. The visual contexts contained items in two color subsets and the ratio of items in these subsets changed with each trial. Participants could freely choose between two targets, one presented in each of the color subsets. Importantly, and in contrast to previous work, color was an irrelevant feature dimension in the task, as the targets were defined by shape. Results showed that participants adapted their target choice to the trial sequence and preferred the target from the smaller color subset, despite the irrelevance of color. These results suggest that observers not only adapt to static repetitions of context configurations, as observed in Studies I-III, but that they also integrate contextual changes into their behavior in visual search (see also Wang & Theeuwes, 2020).

The third and final part of this dissertation (Study V) investigates individual differences in contexts of social perception and broadens the examination of visual contexts to the disciplines of social and personality psychology. Participants were confronted with contexts of untrustworthy and trustworthy face stimuli, accompanied by words which were either congruent, incongruent, or neutral with regard to the contexts. Study V examined how the contexts influenced attention allocation to congruent and incongruent stimuli, and how the personality of different individuals affected the allocation of attention. To this end, the

personality trait victim sensitivity (Gollwitzer, Rothmund, & Süssenbach, 2013) was chosen as a promising moderator. Results revealed that attention allocation, measured by the participants' eye movements, differed between the contexts. Participants generally allocated more attention to trustworthy than to untrustworthy words (longer dwell times, more fixations). However, this difference tended to be more pronounced for untrustworthy contexts, suggesting that the incongruent trustworthy words were prioritized in attention allocation. Furthermore, victim-sensitivity was correlated with increased attention allocation to incongruent stimuli in untrustworthy contexts. These results show that contexts of social perception influence the processing of incongruent and congruent visual information, and that an individual's personality is crucial for these context effects.

In sum, the five studies of the present dissertation demonstrate that the visual system is remarkably sensitive to regularities in the visual context. It is quite efficient in extracting repeated contexts to guide attention to relevant locations when contexts are encountered again (Studies I and II), and it only needs a very limited amount of repeating contextual information to take advantage from the contexts (Study III). It also considers rewards that are signaled by features of the contexts to prioritize processing of high reward contexts. The visual system further adapts to dynamical changes in the contexts (Study IV) and uses contexts of social perception for differential processing of incongruent and congruent stimuli, dependent on the observer's personality (Study V). The present dissertation thus highlights that the visual context is crucial for guiding our attention in numerous situations that we encounter every day. Fortunately, we can take advantage of the visual context, which allows our visual system to cope with its limited processing capacity.

1 INTRODUCTION

Efficiently processing relevant visual information in our environment is an important capability for successfully managing numerous everyday situations. Imagine you are driving in an unknown city, a context crowded with visual information: stoplights, traffic signs, speed limits, pedestrians, and bright and colorful billboards. In this situation, there are many visual stimuli competing for your limited processing resources and navigating through this cluttered visual scene can require a lot of effort. Because the visual system is not capable of simultaneously processing all available visual information (e.g., Broadbent, 1958; Driver, 2001; Lavie & Dalton, 2014), information has to be prioritized, a mechanism known as *selective visual attention*.

In the driving example (see also Chun, 2000), you may want to pay attention to signs showing the correct way, stoplights, signs for speed limits – and you have to be aware of pedestrians stepping suddenly on the road. In addition, you may be on your way to pick up your friend at the train station and you also need to look for him (he usually wears a red jacket). That is, you have certain goals in that situation which you use for actively guiding attention to relevant information (e.g., red stimuli), a mechanism referred to as *top-down* attentional control. When you are passing a colorful billboard, however, your attention might be drawn automatically towards this physically salient visual stimulus, although this was not your goal in that situation. Such an automatic and stimulus-driven orienting of attention is referred to as *bottom-up* attentional control.

The situation seems entirely different when driving through your hometown, as compared to an unknown city. In a familiar environment, you know how to find your way through the visual environment and which critical spots to attend to, and therefore attending to relevant information requires far less effort. That is, based on previous encounters with the visual environment of your hometown, you have learned how to guide your attention efficiently in this context. In such a context, past experiences influence the guidance of your attention, which can neither be explained by bottom-up nor top-down processes sufficiently. In the light of such phenomena, Awh, Belopolsky, and Theeuwes (2012) introduced *selection history* as an additional factor determining attentional selection, resulting from (implicit or explicit) learning mechanisms (Theeuwes, 2018).

The example of driving in a familiar compared to an unfamiliar town shows that the visual context can be used to guide attention. In our visual environment, stimuli usually appear embedded in visual scenes, which follow certain regularities (e.g., Biederman, Mezzanotte, & Rabinowitz, 1982; Le-Hoa Võ & Wolfe, 2015; Palmer, 1975). For instance, when searching for a laptop in a room containing a desk and a bed, observers tended to fixate areas around the desk, whereas searching for a teddy led to fixations in the area of the bed (Võ, Boettcher, & Draschkow, 2019). This result suggests that, in this particular context, observers expected a laptop to appear on the desk and a teddy to appear on the bed. They had probably learned that the objects appeared in these locations in former encounters with similar contexts and used these regularities for guiding their attention.

The main research question of this dissertation is how observers use visual contexts to guide their attention and how they integrate different contextual regularities into their attentional behavior. In line with the examples described above, there is evidence that observers use repeated contexts to guide their attention when they encounter contexts again (Chun & Jiang, 1998). There is also evidence that observers use contexts that change dynamically for adapting their attentional behavior, and it was suggested that individuals differ considerably in how they use visual contexts (Irons & Leber, 2016). While these results stress the importance of the visual context for attention guidance, many aspects of visual contexts are not yet explored. It is unclear how contexts that are associated with motivational value (i.e., reward) are used for guiding attention, and it was not examined whether observers also adapt to changes in the contexts when they are not relevant to them. Furthermore, it is unclear which factors might explain the individual differences observed in context effects. These research gaps are addressed in this dissertation.

1.1 The role of context in visual attention

Former work has demonstrated that regularities in the visual context can have huge impacts on behavior and visual attention guidance (e.g., Chun, 2000; Chun & Jiang, 1998; Goujon, Didierjean, & Thorpe, 2015). In five studies, this dissertation investigates how different contextual regularities affect visual attention. To this end, three different context types are examined. Studies I-III focus on repeated contexts, which reappear over time. Study IV examines dynamically changing contexts, which change in a predictable manner over time. Study V investigates individual differences in context effects using contexts of social perception. On the following pages, the empirical background of these contexts is reviewed and the specific research gaps addressed in this dissertation are identified.

1.1.1 Exploiting repeated contexts in visual search

Many visual contexts appear repeatedly and without significant changes over time. Consider the example of driving in your hometown, introduced in the beginning of this dissertation. It is very likely that the context of your hometown will look about the same in a week as it does today. That is, once you have learned where, for instance, critical spots are located, you can efficiently attend to these critical spots in future encounters with that context. This is because the context and the location of the critical spots within the context are repeating.

The use of repeated contexts for guiding attention was demonstrated in a seminal study by Chun and Jiang (1998). The authors conducted a visual search task and observed that participants responded faster to targets presented in distractor contexts that repeated during the experiment compared to novel contexts that participants had not seen before. However, their participants were not able to discriminate between repeated and novel contexts in a recognition test after the experiment. The authors concluded that observers implicitly learned an association of the repeated distractor contexts and the location of the target embedded in these contexts. This regularity could be extracted and used for guiding attention to the target when encountering repeated contexts again (Chun, 2000; Chun & Jiang, 1998). With that interpretation in mind, Chun and Jiang (1998) named the effect *contextual cueing.* Contextual cueing is considered a *statistical learning* effect (see section 1.2.2). That is, observers extract regularities from their visual environment and adjust their behavior accordingly (Goujon et al., 2015).

Eye movement studies suggest that it is indeed attention guidance that is facilitated by the repeated distractor contexts. Participants not only responded faster in repeated contexts, but they also made more efficient eye movements to the target, manifesting as more efficient scan paths and fewer fixations (Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012). In addition, EEG studies observed an increased N2pc component in repeated compared to novel contexts, an EEG component suggesting that selective visual attention was modulated in repeated contexts (Luck & Hillyard, 1994; Schankin & Schubö, 2009, 2010).

Although many contexts in our visual environment are repeating, a context might not always repeat entirely over time. It is quite frequent that only some parts of a context remain constant whereas others are changing. When you reencounter your hometown after a week, nothing may have changed. However, when you spend a decade abroad and return after ten years, it is likely that the context has changed to some extent. There might be new buildings or roads, which are unknown to you when you return. Nevertheless, it is still likely that you are better in navigating in your hometown compared to a novel town even after ten years, as you might be able to use the remaining repeated information. In that sense, contextual cueing studies observed that participants could exploit the repeated contexts also when only parts of the contexts were repeating (Jiang & Leung, 2005; Olson & Chun, 2002; Song & Jiang, 2005).

The extent to which participants exploit repeated contexts for guiding their attention, however, depends on numerous factors (see Goujon et al., 2015, for a review). For instance, homogeneity of the distractor contexts was reported to increase the contextual cueing effect (i.e., the response time advantage of repeated over novel contexts; Feldmann-Wüstefeld & Schubö, 2014), but, on the other side, conditions of high working memory load were detrimental to contextual cueing (Manginelli, Geringswald, & Pollmann, 2012). Thus, the conditions under which observers encounter repeated contexts might heavily determine how the repeated contextual information is extracted and integrated into behavior. Recent studies demonstrated that also motivational value, i.e., reward, could boost the exploitation of repeated contexts. When participants received a reward feedback for responding correctly, the contextual cueing effect emerged earlier compared to receiving no reward (Tseng & Lleras, 2013; see also Pollmann, Eštočinová, Sommer, Chelazzi, & Zinke, 2016; Sharifian, Contier, Preuschhof, & Pollmann, 2017). Tseng and Lleras (2013) speculated that the reward feedback facilitated the learning of repeated contexts, presumably because receiving a reward led to a boost in arousal strengthening memory consolidation of learned contextual information.

In the study of Tseng & Lleras, the participants were informed about the magnitude of the reward after giving a response. In novel contexts, they were therefore not able to predict the reward magnitude during their search. In our natural visual environment however, we can usually predict the availability of a reward by features of the context. That is, we often can associate a context with a certain motivational value even if we have never encountered this particular context before. For instance, when heavy-alcohol-users are encountering the context of a liquor store, they might predict reward (i.e., the effects of alcohol) in this context no matter whether they had been in this particular store before or not. In this example, it seems likely that attention guidance would be affected by the prediction of reward, even in a "novel" context (Albertella, Watson, Yücel, & Le Pelley, 2019).

It seems plausible that the extraction of repeated context configurations might be facilitated in contexts predicting high compared to low reward. However, the influence of reward-predicting context features on the use of repeated contexts is unexplored so far. The main part of the present dissertation (Studies I, II, and III) focuses on the role of context features signaling reward in the exploitation of repeated contexts. Study I examines how reward-predicting but task-irrelevant colors modulate context learning. Study II investigates the effect of reward-predicting distractor orientations, a context feature which is task-relevant, and examines whether reward has persistent effects on context learning. Study III investigates the influence of reward-predicting colors in contexts that repeated entirely and in contexts that repeated only in part.

1.1.2 Adapting to dynamically changing contexts

While many contexts repeat over time, others are constantly changing. When driving in a city at different times of the day, the visual context will differ dramatically. Early in the morning, the environment might still be dark. During the day it gets gradually brighter, but towards the evening it gets darker again. That is, the visual context is dynamically changing from dark towards bright and back. This dynamical change might affect your visual attention fundamentally, as, for instance, it might be easier to detect dark-clothed pedestrians in the bright context at daylight compared to the dark context at night. To drive safely, you might have to adapt your attentional control to the changing lighting conditions of the context (Konstantopoulos, Chapman, & Crundall, 2010).

Irons and Leber (2016) investigated the adaptation of attentional control in a dynamically changing visual context (see also Hansen, Irons, & Leber, 2019; Irons & Leber, 2018). Using a novel paradigm, the authors let their participants choose between two available targets embedded in a context of distractors. The targets were defined by a combination of color and size (small in size and blue or red in color). One target was always red and one was blue. Some of the distractors changed their color dynamically from trial to trial. They started being colored like one of the targets and then changed their color stepwise with each trial towards the color of the second target. The authors observed that the participants adapted their target choice to the colors of the distractors in the context. They preferred selecting the target, whose color was most different to the distractors and switched their preference during the trial sequence. The authors concluded that participants adapted their target choice in order to maximize task performance, since it was more efficient to locate a target that differed in color to the distractor context. However, some participants also barely adapted. The authors suggested that these individuals refrained from adapting in order minimize effort.

The results of Irons and Leber (2016) suggest that, in an unconstrained environment, observers integrate a dynamical environmental change into their behavior. The change appeared on a relevant feature dimension (e.g., Krummenacher & Müller, 2012) in their task, since the target was defined by a combination of color and shape. The authors interpreted that the dynamical color change gave rise to an adaptation of attentional control strategies, that is, search strategies the observers implemented to perform the task. Alternatively however, one might think that observers adapt to changes in their environment spontaneously, and that they even adapt when the change is not relevant for accomplishing the task (see Wang & Theeuwes, 2020). Little is known about such a behavioral adaptation to an irrelevant change in the visual environment, and this research gap is addressed in this dissertation with Study IV.

1.1.3 Inter-individual differences in attention allocation: The context of social perception

Irons and Leber (2016) observed that individuals differed considerably in how they adapted their behavior in an unconstrained visual context. The last study of this dissertation (Study V) focusses on the influence of inter-personal differences on visual attention allocation and broadens the perspective on visual contexts in an interdisciplinary way. In this study, the idea that participants adapt their attention allocation to contextual regularities is connected to concepts of social and personality psychology.

When you are driving in a city, it is very likely that you are sharing the road with other people, making social perception another characteristic of this context. How you expect the other drivers to behave can be an important factor of how you allocate your visual attention. For instance, when you are driving behind a car of a driving school and you recognize the face of an insecure-looking young student behind the steering wheel, you might expect that the driver is inexperienced. To be able to react to the student driver's behavior, you might deploy increased attention to the car in front of you. When you notice that the driving instructor is driving rather than the student, this behavior might be entirely different and you might deploy less attention to the car in front of you, as you trust in the driving abilities of the instructor. Thus, attention allocation in this context might also be determined by stimuli that are relevant for social perception.

In this example, inter-personal differences could play a huge role in how attention is deployed. When individuals generally distrust the driving abilities of the drivers around them, they might deploy their visual attention completely different compared to an individual that generally trusts in the abilities of other drivers. In the disciplines of social and personality psychology, the personality trait *victim sensitivity* is related to a general tendency to distrust others (Gollwitzer et al., 2013). It is assumed that victim sensitivity can modulate social perception by biasing how “contextual cues” signaling untrustworthiness (e.g., untrustworthy faces in the visual environment) are processed (Gollwitzer et al., 2013; Gollwitzer, Rothmund, Alt, & Jekel, 2012). Recently, it was observed that victim sensitive individuals showed biases in remembering trustworthiness-related information (Süssenbach, Gollwitzer, Mieth, Buchner, & Bell, 2016). Since it is well established that visual selective attention has a strong relation to memory (e.g., Heuer & Schubö, 2018), this finding might imply that these individuals also show biases in their attention allocation in contexts of social perception. How individuals with varying degrees of victim sensitivity deploy their visual attention in contexts of social perception is a research gap that the last study of this dissertation (Study V) is addressing. Fig. 1 provides a summarizing overview of research gaps and research questions that were studied in the present dissertation.

	Main research question: ***How do observers use visual contexts to guide their attention?***		
	Studies I-III: Repeated contexts	**Study IV: Dynamically changing contexts**	**Study V: Contexts of social perception**
Background	Observers exploit repeating contexts to guide their attention (contextual cueing).	Observers adapt their behavior to task-relevant contextual changes.	Personality (victim sensitivity) was reported to bias memory of social information.
Research gaps	It is unexplored how reward-predicting context features modulate contextual cueing.	It is unclear whether observers also adapt to a change on an irrelevant feature dimension.	In contexts of social perception, attentional biases of victim-sensitive individuals are unex-plored.
Research questions	How do observers exploit repeating contexts in their attention guidance? How do observers incorporate reward-predicting context features in the guidance of attention?	How do observers use dynamical changes in the visual context? How do observers adapt to irrelevant contextual regularities?	Study visual contexts with an interdisciplinary perspective: How does an observer's personality determine attention allocation in visual contexts?

Fig. 1. Background, research gaps, and research questions of the three parts of this dissertation. The main part (Studies I-III, left column) studies repeated contexts that reappear over time. The second part focuses on dynamically changing contexts (Study IV, middle column), and the third part investigates individual differences in contexts of social perception (Study V, right column).

1.2 Background: Selection history

Contextual cueing, which is examined in the first part of this dissertation (Fig. 1, left column), is considered a *statistical learning* effect (Goujon et al., 2015). Statistical learning is one of several known effects of selection history (for reviews on selection history, see Awh et al., 2012; Failing & Theeuwes, 2018; Theeuwes, 2018, 2019). Awh et al. (2012) introduced selection history as a factor for determining attentional selection. Based on previous experiences, like previous encounters with a visual context, an observer's attention can be strongly biased towards stimulus features or locations. These biases can be independent from current goals and the physical saliency of stimuli (e.g., Kadel, Feldmann-Wüstefeld, & Schubö, 2017; Le Pelley, Pearson, Griffiths, & Beesley, 2015). Awh et al. (2012) suggested that biases of selection history feed into an integrated priority map together with the current goals (top-down) and the physical saliency (bottom-up). The largest activation on the integrated priority map determines the allocation of attention (e.g., Itti & Koch, 2001). Reward, which is added to contextual cueing in the first part of this dissertation, is also considered an effect of selection history. For the research questions of the present dissertation, the effects of *reward* and the effects of *statistical learning* are therefore of special relevance. These are briefly outlined in the following sections.

1.2.1 Reward

The effects of *reward*, i.e., motivational value, on visual attention have attracted increasing interest among vision researchers during the past years (Anderson, 2016; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Failing & Theeuwes, 2018; Le Pelley, Mitchell, Beesley, George, & Wills, 2016). Rewarding participants for a good task performance can result in a general motivational boost, which can increase performance in visual tasks (Failing & Theeuwes, 2018). For instance, perceptual sensitivity was increased in a spatial cueing task, when participants received rewards linked to their task performance (Engelmann & Pessoa, 2007).

However, reward was not only reported to lead to unspecific boosts in task performance, but also to affect visual attention more directly. There is evidence that reward can lead to prioritized processing of both features and locations associated with reward in visual search. When participants searched for a color singleton target, task performance was increased when the target's color signaled a high compared to a low reward (Kiss, Driver, & Eimer, 2009). The authors also observed an enlarged N2pc component on high reward trials, suggesting that selective visual attention was modulated by reward (Luck & Hillyard, 1994). When features of (to-be-ignored) distractors signaled high compared to low reward, task performance was impaired, which also suggests that the reward-signaling stimuli captured attention in visual search (e.g., Anderson, Laurent, & Yantis, 2013; Feldmann-Wüstefeld, Brandhofer, & Schubö, 2016; Le Pelley et al., 2015).

Reward can even be strong enough to overrule an observer's intentions in the task at hand, as Le Pelley et al. (2015) demonstrated (see also Failing, Nissens, Pearson, Le Pelley, & Theeuwes, 2015; Failing & Theeuwes, 2017; Koenig, Kadel, Uengoer, Schubö, & Lachnit, 2017). In Le Pelley et al.'s study, participants searched for a shape target, while the color of an irrelevant distractor signaled reward. Importantly, although the distractor signaled reward, fixating the distractor was coupled to an omission of reward. Nevertheless, the authors observed that high-reward distractors biased eye movements and were fixated more frequently during search. That is, reward-predicting distractors led to attentional capture by merely signaling the availability of reward, although this was counterproductive for receiving the reward in the end.

The studies described so far demonstrate that reward can bias visual attention when it is coupled to specific features of stimuli. Hickey, Chelazzi, and Theeuwes (2014) showed that reward can also alter processing of spatial locations in visual search. In their study, participants received a high or a low reward feedback for responding correctly. After receiving a high reward, they responded faster when the target reappeared at the same location in the next trial. The authors concluded that reward facilitated the return of attention to locations that held a target followed by a high reward feedback. This suggests that attention is guided to rewarded locations in visual search.

In sum, reward can bias attention towards reward-predicting features and locations, and, dependent on the current goals of the observer, reward can be beneficial or detrimental to task performance in visual search. The results described above suggest that the presence of stimuli signaling reward seems to play an important role in how we process our visual environment, independent from our current goals and the physical saliency of stimuli.

1.2.2 Statistical learning

Not only reward but also statistical regularities in the visual environment have been demonstrated to influence attentional processing of features and locations. There is growing evidence that observers extract regularities from their environment spontaneously and integrate these regularities in their behavior and the guidance of attention, a process known as *statistical learning* (e.g., Goujon et al., 2015; Theeuwes, 2018).

For example, there is evidence that participants were faster in detecting the target at high-probability compared to low-probability locations in visual search (Geng & Behrmann, 2005; Jiang, Swallow, Won, Cistera, & Rosenbaum, 2015). The use of high-probability target locations might seem less surprising, since finding the target is the goal of the task and the target location is therefore highly relevant for the task. However, recent studies demonstrated that observers also extracted regularities concerning distractor locations, that is, regularities of irrelevant visual stimuli. When distractors appeared more frequently at specific locations in visual search, participants learned to avoid these locations during search, which was also reflected in their oculomotor behavior in some studies (Di Caro, Theeuwes, & Della Libera, 2019; Ferrante et al., 2018; Wang & Theeuwes, 2018a, 2018b, 2018c; see also Gaspelin & Luck, 2018).

Similar to the effects of reward, there is evidence that statistical learning can not only influence processing of spatial locations but also processing of specific features. When the target frequently appeared in a specific color, observers were reported to prioritize this color during the experiment, leading to increased attentional capture of stimuli presented in the high-probability color (Cosman & Vecera, 2014). Furthermore, regularities in the colors of distractors were also reported to bias attentional selection. When the distractors were frequently presented in a specific color during the experiment, observers showed increased attentional suppression of distractors presented in the frequent color compared to less frequent colors (Stilwell, Bahle, & Vecera, 2019, see also Failing, Feldmann-Wüstefeld, Wang, Olivers, & Theeuwes, 2019; Won, Kosoyan, & Geng, 2019). These findings suggest that observers adapt to regularities of both targets and distractors in visual search and that regularities of locations and features are extracted and integrated into the observers' behavior.

In sum, the findings described in this section suggest that observers are remarkably sensitive to regularities in their environment, as there is evidence that observers use several statistical regularities for adjusting attention guidance accordingly.

1.3 Experimental approaches

The five studies of the present dissertation aim at understanding how observers use different contextual regularities to deploy their limited attentional resources. To this end, Studies I-IV used *visual search paradigms* (e.g., Wolfe, 1994; Wolfe, Cave, & Franzel, 1989). In these paradigms, observers are instructed to locate predefined targets among displays containing several distractor items. Visual search paradigms allow quantification of the capacity limitations of the visual system by measuring task performance using, for instance, response times and comparing them among differently composed search displays (Wolfe, 2014). In the visual search paradigms used in this dissertation, the distractor items correspond to the visual context. That is, these elements compose a visual scene in which targets are embedded. In Studies I-III, the distractor contexts were repeating or generated newly during the experiments (contextual cueing, see section 1.1.1). This was done to investigate of the effects of repeated visual contexts on behavior in visual search. In Study IV, the distractors were dynamically changing from trial to trial in a predictable sequence, which allowed to investigate how observers use dynamically changing contexts (see section 1.1.2).

To draw conclusions about the effects of the distractor contexts on visual attention, two types of measures were examined in this dissertation: Behavioral performance measures and eye movements using eye tracking. As measures of behavioral performance, Studies I-III primarily examined response times for reporting the target in visual search. The underlying assumption was that response times for *reporting* a target are strongly related to the difficulty of *finding* a target in a certain context. Studies I-III also analyzed co-recorded eye movements during visual search, which could provide further insights of how attention guidance was affected by the contexts (see next section). Study IV, in contrast, primarily investigated the choice between two available targets in visual search. It was assumed that the distractor context might affect how participants choose between the targets, which allowed conclusions about the adaptation of search behavior to the contexts (Irons & Leber, 2016).

In contrast to Studies I-IV, Study V did not implement a visual search paradigm. In a newly developed paradigm, participants were confronted with face stimuli, which composed a context of social perception and were accompanied by other stimuli. Study V primarily investigated eye movements, whereas behavioral responses were not of primary interest. It examined how the individuals' eye movement patterns were dependent on the contexts, and how individuals with different personalities (victim sensitivity, see section 1.1.3) differed in their eye movements.

In the next section, the rationale of using eye tracking for measuring visual attention is outlined. In the following sections, the used paradigms and specific aims related to the paradigms are described, followed by summaries of the individual studies.

1.3.1 Measuring visual attention using eye tracking

In his famous classical studies, Yarbus (1967) examined the eye movements of observers while they were inspecting visual scenes. The observers' viewing patterns were visualized by "drawing" the path the eyes travelled (*scan path*) onto the visual contexts, revealing that the scan path of the observers largely depended on the instructions they received for inspecting the contexts. For instance, when the observers were asked to give the age of people contained in a drawing, the eyes were mostly moved to the faces of the people, whereas an instruction to remember the people's and objects' locations led to eye movements all over the scene. These results showed that observers directed their eyes to locations in the scenes that were *relevant* for them, suggesting that an observer's visual attention guidance is tightly coupled to the executed eye movements towards attended locations (Deubel & Schneider, 1996). Yarbus also noticed that the participants' viewing patterns were characterized by two distinct components. The eyes either shortly rested at relevant locations (known as *fixations*) or moved quickly between locations of interest (known as *saccades*).

Although visual attention seems to be tightly linked to eye movements, observers are also known to shift their attention without moving their eyes. This was, for instance, demonstrated in spatial cueing experiments in which participants usually shift their attention while keeping their gaze stable on a fixation cross at screen center (Posner, 1980, 2016). The allocation of attention with accompanied eye movements is referred to as *overt attention allocation*, whereas attention shifts without eye movements are known as *covert attention allocation*. However, although attention can principally be directed without the need for eye movements, this might rather be the exception than the rule in naturalistic situations, in which eye movements usually seem quite tightly linked to attention shifts (Beesley, Pearson, & Le Pelley, 2019). This suggests that inspecting eye movements can be a useful tool for measuring visual attention guidance of observers when they are inspecting visual contexts.

In the present dissertation, co-recorded eye movements were evaluated in Studies I-III, which used visual search paradigms. Inspecting eye movements in visual search tasks can add important insights in addition to behavioral performance measures, e.g., response times. While response times do not only include attentional processes but also all other processes happening before the participants give a response (e.g., selecting a response), eye tracking analyses can add insights about the guidance of (overt) attention during the search process (Zhao et al., 2012). In addition to response times for reporting the target in visual search, Studies I-III therefore used eye movements to quantify the *efficiency of attention guidance* during visual search. To this end, the number of fixations during search (*fixation count*) was evaluated, assuming that an "efficient" search needed fewer fixations than an "inefficient" search did (e.g., Tseng & Li, 2004). The fixation count thus quantified the efficiency of the complete search process. In addition to the fixation count, Study I also investigated the distance of the first fixation to the target location. The distance of the first fixation to the target is considered an early component of search efficiency, that is, a measure for search efficiency at the beginning of the search process (Zhao et al., 2012).

Study V also used eye movements as a measure for attention allocation, but, in contrast to Studies I-III, as primary dependent variables. Study V sought to investigate the prioritization of different available stimuli during attention allocation, depended on the context in which the stimuli were appearing. To this end, different *areas of interest* (AOIs) were defined within the contexts, containing different types of stimuli. By comparing the eye movements between these AOIs, Study V examined how attention allocation differed between the stimuli. Separately for each AOI, Study V considered four eye-tracking measures for operationalizing the priority of stimuli in overt attention allocation. By measuring the fixation count in each AOI, the duration of the first fixation, and the time the eyes spent fixating an AOI (*dwell time*), Study V measured how specific stimuli differed in their priority for being attended. It was assumed that prioritized processing of stimuli would result in longer dwell times and more fixations for inspecting these stimuli. In addition, Study V evaluated which AOI was fixated first, assuming that prioritized visual information would be considered first in the guidance of visual attention.

In sum, the studies of the present dissertation used eye movement recordings to operationalize the guidance of visual attention and to measure the priority in attention allocation. However, only Studies I-III and V used eye tracking, whereas Study IV solely relied on behavioral response measures (target choice between two targets, response times). It should be noted that, although eye tracking comes with various benefits, it does incorporate costs in terms of requiring quite expensive equipment and additional time (Beesley et al., 2019). Study IV implemented a variation of a novel paradigm, which was, as a first step for this paradigm, implemented without the use of eye tracking. In the following sections, the different paradigms used in this dissertation are outlined.

1.3.2 Study I-III: The contextual cueing paradigm

Studies I-III focused on how context features predicting motivational value influence the use of repeated contexts. To this end, these studies implemented variations of the classical *contextual cueing paradigm* (cf. section 1.1.1), a visual search paradigm which has been frequently implemented for investigating the use of repeated contexts in the past 20 years

(Chun & Jiang, 1998; for reviews, see Chun, 2000; Goujon et al., 2015; Sisk, Remington, & Jiang, 2019). As in the original paradigm, participants in Studies I-III were instructed to search for one specific target ("T"-shape) among a context configuration of distractors ("L"-shapes). Since the target was presented in every trial, participants were not asked to respond to the presence versus absence of the target. Instead, the target was tilted to the left or right, which randomly varied in each trial. Participants reported whether the target was tilted to the left or right by pressing a corresponding button.

Unbeknown to the participants, some of the distractor contexts were repeating during the experiments ("repeated contexts"). In these distractor contexts, the arrangement of distractors reappeared exactly as it was shown before, with the target appearing at the exact same location. Thus, participants could learn an association of the repeated distractor contexts and the target location and could use this information to guide their attention to the target. The orientation of the target was however varying randomly from to trial so that participants could not learn to associate a target orientation, i.e., a response, with the repeated contexts. During the experiments, the repeated contexts were presented intermixed with contexts that were generated randomly for each trial and did not repeat ("novel contexts"). By comparing response times and eye movements between repeated and novel contexts, Studies I-III could examine how the observers used the repeating contexts in their search behavior.

As a crucial modification to the original paradigm, Studies I-III added a reward feedback for correct responses in every trial. There is evidence that assigning a reward feedback to repeated contexts can lead to an earlier contextual cueing effect, probably because the reward feedback strengthens the memory traces of repeated contexts in learning (e.g., Tseng & Lleras, 2013; see section 1.1.1). Studies I-III built upon these earlier results and introduced reward-predicting *context features*, which enabled the prediction of the reward in both, repeated and novel contexts with display onset. It was assumed that these features might have a considerable influence on how the repeated contextual information was extracted and integrated into search behavior.

Studies I-III made another important modification to the original contextual cueing paradigm. In contrast to many previous studies, the same target locations were used for novel and repeated contexts and contexts with different reward magnitudes. Thus, a certain target location was only predictive of holding the target, but neither of context novelty nor of the reward magnitude. This manipulation ruled out that individual target locations were weighted differently by reward. When reward feedback is added to a visual task, the visual system has been demonstrated to be remarkably sensitive at relating reward to repeating spatial locations in the visual environment (e.g., Hickey, Chelazzi, & Theeuwes, 2010, 2011). That is, when certain target locations are more frequently followed by a reward feedback than others, participants might associate reward with the target location. This might lead to increased attentional weights at these locations facilitating the return of visual attention to these locations when they hold a target again (Schlagbauer, Geyer, Müller, & Zehetleitner, 2014).

Most contextual cueing studies used separate sets of target locations for repeated and for novel contexts to ensure that repeated contexts were unambiguously associated with individual target locations. However, when reward feedback follows repeated contexts with unique target locations in contextual cueing, the reward is not only coupled to the repeated context configuration but also to the unique target location embedded in the context. Thus, observers could associate the reward with the repeated contexts, the repeated target locations, or both (Sharifian et al., 2017). Therefore, using separate target locations for novel and repeated contexts might complicate the interpretation of reward effects in contextual cueing. By sharing target locations, Studies I-III could overcome this issue.

Study I investigated the influence of a salient but task-irrelevant context feature (color) signaling reward on contextual cueing. Half of the context items were homogeneously colored and color signaled the magnitude of a reward given for correct responses. Color was task-irrelevant in Study I, because the T-junction defined the target and participants had to judge the orientation of the T for responding. Thus, color was neither required for finding the target nor for responding. In addition, the target was colored in 50% of trials which made searching by color an inefficient strategy in the experiment.

Study II built upon Study I and coupled reward to a less salient but task-relevant context feature. Reward was associated with the main orientation of the distractors in the display. Orientation is a task-relevant context feature, since participants have to judge the target's item orientation for responding. In addition, the number of context repetitions was doubled in Study II compared to Study I. This allowed to investigate whether reward led to an earlier emerging but asymptotically similar contextual cueing effect, or whether contextual cueing was increased persistently by reward.

Study III investigated whether observers show contextual cueing not only for contexts in which the entire global configuration repeats but also when only a limited local context surrounding the target is repeated. It was examined whether observers use local and global context repetitions for finding the target in a similar manner, and whether reward affects the learning of local and global contexts similarly. In Study III, three context types were used. In addition to the entirely repeated and entirely novel contexts used in Studies I and II, Study III included "local" repeated contexts in which only a patch surrounding the target was repeated. The remaining context was varying randomly with each context repetition. As in Study I, reward magnitude was coupled to task-irrelevant colors. The comparison of local, global, and novel contexts allowed to investigate whether participants could use local and global contexts in a similar manner to detect the target. By comparing low and high reward contexts, Study III could examine whether reward affected context learning in local and global contexts similarly.

In sum, Studies I-III investigated how reward-predicting context features in the observers' visual environment alter the way in which repeated context configurations are processed. To this end, these studies used contextual cueing paradigms, examining how repeated contextual information was integrated into the observers' search behavior.

1.3.3 Study IV: The adaptive choice visual search paradigm

Study IV investigated how observers integrate a dynamical change in the visual context into their behavior in visual search. To this end, Study IV implemented a modified version of the *adaptive choice visual search paradigm* (ACVS; Irons & Leber, 2016; see section 1.1.2). Compared to contextual cueing, the ACVS paradigm is a rather novel paradigm which was developed as a fresh approach to study the adaptation of attentional control in a rather unconstrained visual search paradigm. In classical visual search tasks, observers usually have to indicate the presence or absence of (mostly) one predefined target, which might not always represent the search situation in naturalistic environments. In many visual searches we perform in our daily lives, there is not one but often numerous targets available. In such a situation, we do not only have to find one target (e.g., search for a banana in the supermarket), but also have to *decide* between available targets (e.g., take the rather green or the yellow one).

The ACVS paradigm formalizes the decision between two targets in a controlled visual search task in the laboratory. In the original paradigm (Irons & Leber, 2016), participants were instructed to decide between two targets; small squares, one in red color and one in blue (see section 1.1.2). Participants had to search for a combination of color and size because some of the distractors were colored in red and blue and there were also some small green distractors contained in the search context. The authors then gradually changed the colors of some distractors in the display, varying the difficulty of finding either target.

Study IV made a crucial modification to the original paradigm. Like in the original paradigm, the targets always differed in their color, and the ratio of distractors that were colored like each target changed dynamically during the trial sequence. In Study IV, however, participants were instructed to choose between two *shape singleton* targets (diamonds among circles). Therefore, the targets could be recognized with little or no effort by their differing shape compared to all distractors in the search contexts (Treisman, 1988; Treisman & Gelade, 1980; Wolfe, 2020a, 2020b). In contrast to the original ACVS paradigm, participants did not need to consider color to find the targets in the modified paradigm in Study IV. That is, color was *irrelevant* to the task of finding the target. Nevertheless, participants could use color for determining their target choice because the targets always differed in their color and the color of one target was occasionally more unique than the other target's color. Study IV examined whether participants also adapted their target choice to color, when color was not a target-defining feature in the task.

In sum, Study IV used a modified ACVS paradigm to investigate the impact of an irrelevant contextual change on the choice between two available targets in visual search. By investigating the *target choice* of the observers, the ACVS paradigm of Study IV allowed conclusions about how observers adapted their search behavior to the changing contexts.

1.3.4 Study V: Attention allocation in the context of social perception

Study V investigated the influence of the visual context on attention allocation in an interdisciplinary context. To this end, Study V examined how observers prioritized different stimuli in contexts of social perception, and how individuals with differing personalities (victim sensitivity, see section 1.1.3) differed in their attention allocation. Study V developed a novel paradigm in a cooperation project, connecting concepts of personality and social psychology with classical laboratory paradigms from experimental psychology. In this paradigm, participants were confronted with faces presented at the center of a computer screen. Faces are considered very strong contextual cues for signaling untrustworthiness (Said, Dotsch, & Todorov, 2010) and the faces of Study V were selected for being either "trustworthy" or "untrustworthy". After a short time span, the faces were accompanied by four words. Similar to the faces, also the words were tested for trustworthiness and were either congruent, incongruent or neutral with regard to the presented face. Thus, the face at screen center composed a context of social perception in Study V, and the words were stimuli contained in the context. Study V examined how the eye movement pattern for congruent and incongruent words differed dependent on the face at screen center and whether individuals with different degrees of victim sensitivity differed in their eye movements.

In sum, Study V investigated contexts of social perception and developed a novel paradigm, connected to the fields of social and personality psychology. The last study therefore concludes this dissertation with a transfer of visual context effects to other psychological disciplines.

2 STUDY SUMMARIES

On the following pages, the five studies of the present dissertation are summarized. The references to the original articles are given before the individual summary of each study starts.

2.1 Study I: Reward-predicting context features facilitate contextual cueing

Reference

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision, 19*(3), 1–18. https://doi.org/10.1167/19.3.10

Study summary

Former work has demonstrated that contextual cueing (CC; Chun & Jiang, 1998; see sections 1.1.1, 1.3.2) can be modulated by reward. Tseng and Lleras (2013) associated reward feedback with specific repeated contexts and observed that CC appeared earlier in repeated contexts followed by reward than in contexts followed by no reward. They concluded that participants learned an association between the reward and the distractor contexts and assumed that this association speeded the learning of repeated contexts, presumably because receiving a reward feedback led to an increase in arousal.

In Study I, we built upon this finding and introduced a new manipulation of reward in the CC paradigm. When we assume that participants learned an association of a repeated distractor context and a reward in Tseng and Lleras' study, they would have been able to predict the reward from the distractors in repeated contexts before they located the target. In novel contexts, however, participants could not predict the reward magnitude, since these contexts were generated randomly. In Study I, we enabled the prediction of reward in both repeated and novel contexts by associating reward with a salient context feature (color) contained in both context types. We expected that the prediction of a high reward would lead to an unspecific boost of task performance, visible as faster responses in novel and repeated contexts, and that reward increased the contextual cueing effect by facilitating learning of repeated contexts. In addition to response times, we analyzed co-recorded eye movements (distance of first fixation to the target, fixation count) as a measure for the efficiency of attention guidance during visual search (see section 1.3.1).

Fig. 2A depicts the experimental design of Study I. We conducted a standard CC task with half of the contexts repeating in each block. Half of the items in each context were presented in a color reliably signaling the reward magnitude (low, medium or high) that was given for correct responses. Thus, participants could predict the reward from the color in both novel and repeated contexts with display onset. The target was colored in half of the contexts to prevent participants from attending to colored or gray items only (cf. Beesley, Hanafi, Vadillo, Shanks, & Livesey, 2018; Jiang & Leung, 2005).

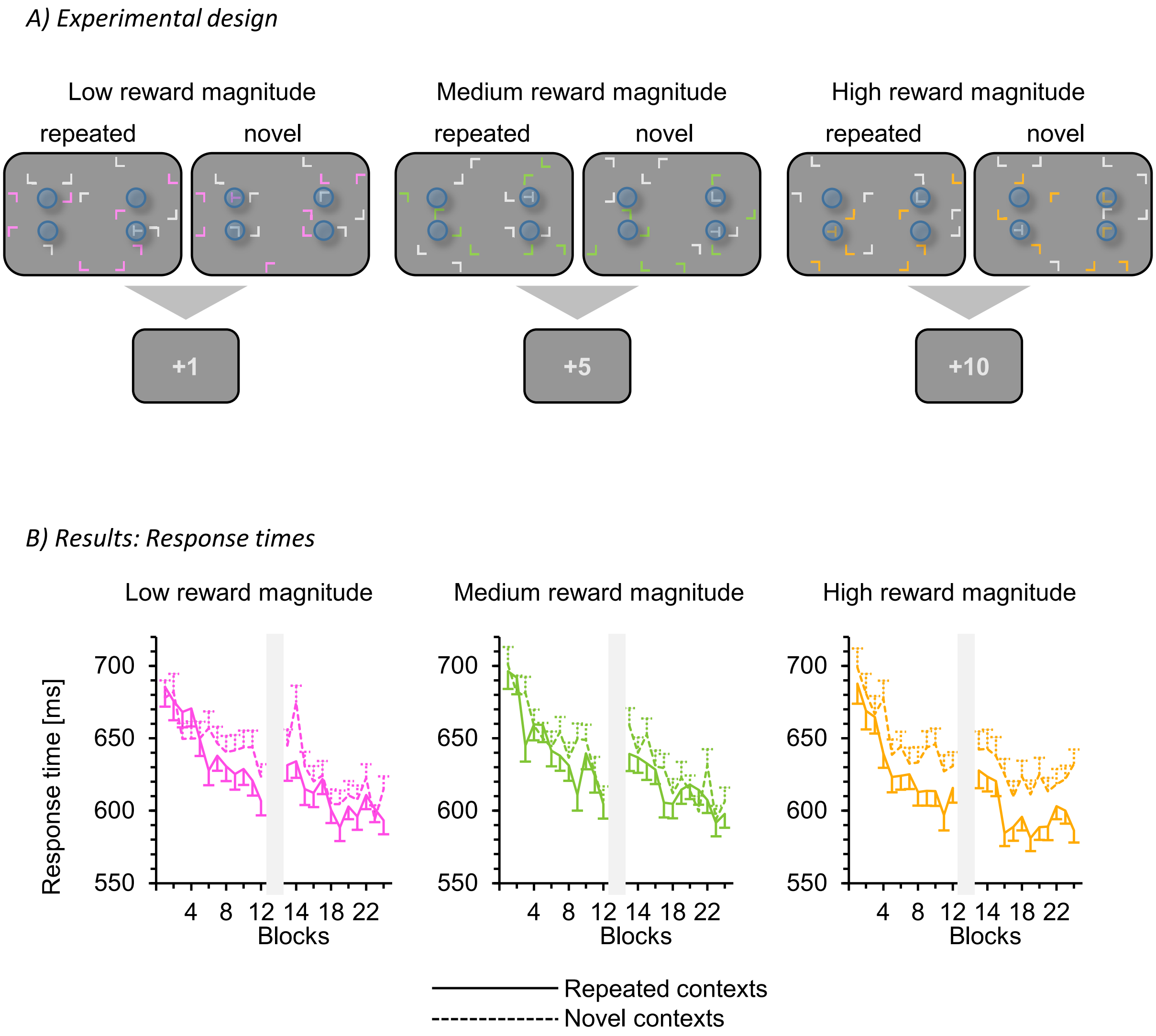

Fig. 2. (A) Experimental design of Study I with exemplary search contexts. Participants searched the T-target among the contexts of L-distractors and reported the T's orientation, which varied randomly in every trial. Half of the contexts repeated, half were novel (contextual cueing paradigm). Half of the items were presented in a color which signaled either low, medium or high reward magnitude given for correct responses (color-reward association balanced across participants). The blue circles were not visible in the experiment and indicate potential target locations. The same locations were used in novel and repeated contexts and in contexts of all reward magnitudes. (B) Observed response times (RTs) in Study I, separately for low (left panel), medium (middle), and high reward magnitude (right). Dashed lines depict RTs for novel, solid lines for repeated contexts. The experiment was divided into two sessions of equal length on separate days (max. one day in between; gap indicated by the gray bar). Error bars show the standard error of the mean. (Figures reproduced from Bergmann, Koch, & Schubö, 2019.)

We observed contextual cueing, measured by faster responses in repeated compared to novel contexts (see the gaps between the dashed and solid lines in Fig. 2B). The CC effect was most pronounced in contexts that contained the color signaling high reward (Fig. 2B, right panel). This was due to faster responses in repeated high reward contexts. Responses in novel contexts were not affected by reward. Interestingly, CC was largely reduced in low reward and virtually absent in medium reward contexts. We could observe a similar pattern of results in the participants' eye movements. In repeated contexts that contained the color predicting high reward, participants made fewer fixations than in contexts predicting low or medium reward, and also their first fixation landed closer to the target in these contexts.

Based on these results, we concluded that the expectation of reward boosted the CC effect, probably because of an increase in arousal (cf. Tseng & Lleras, 2013). We suggested that participants allocated their limited learning resources to the high reward contexts, which could explain why CC was absent or largely reduced in medium and low reward contexts (see also Pollmann et al., 2016). Because reward did not affect response times or eye movements in novel contexts, we concluded that reward rather strengthened learning of the repeated contexts than resulting in an unspecific performance benefit. The finding that faster responses went along with more efficient eye movements to the target led us to the conclusion that the enlarged contextual cueing effect in high reward contexts was due to more efficient attention guidance to the target.

In sum, Study I introduced a reward-predicting context feature (color) to the contextual cueing paradigm and demonstrated that a context feature predicting high reward facilitated the learning of repeated contexts. The results suggest that expecting a reward sensitizes observers to the detection of regularities in their visual environment.

2.2 Study II: Contextual cueing is persistently boosted by task-relevant context features signaling reward

Reference

Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision Research, 171*, 53–63. https://doi.org/10.1016/j.visres.2020.03.010

Study summary

Study I demonstrated that a reward-predicting context feature, i.e., color, led to an increased contextual cueing effect. Color was a task-irrelevant context feature in Study I, since the target was defined by shape (T among Ls) and color was not required to differentiate the target from the distractors. The correct response was also independent from color because participants responded by reporting the item orientation of the target, which varied randomly in each trial. Study II extended the results of Study I by examining whether task-relevant context features led to similar facilitating effects. In addition, Study II investigated the time course of the reward effects more closely. The results of Study I visually suggested that reward led to a persistent advantage in contextual cueing that manifested towards the end of the experiment (see Fig. 2B). Tseng and Lleras (2013), in contrast, had concluded that reward led to an earlier emerging but asymptotically similar CC effect, rather than to a persistent boost of the effect. Study II aimed at clarifying whether reward persistently decreased the response time curves on an asymptotical level, or whether learning was only speeded but asymptotical performance was unaffected.

Fig. 3A depicts the experimental design of Study II. As in Study I, participants performed a contextual cueing task, searching for a T among context configurations of Ls. In contrast to Study I, however, all items were presented in gray. In Study II, the distractor contexts were comparably homogeneous, because 80 % of the Ls were presented in the same orientation (cf. Feldmann-Wüstefeld & Schubö, 2014). The predominant distractor orientation signaled the reward magnitude participants could receive in each trial (low, medium or high), allowing observers to predict the reward magnitude with display onset. Orientation is a task-relevant context feature: Although distractor orientation does not help to find the target (defined by the T-junction), participants have to judge the randomly varying orientation of the target when responding. In Study II, the number of context repetitions was doubled compared to Study I (48 vs. 24). This allowed for a precise analysis of the persistence of the reward effects. As in Study I, participants performed two sessions on separate days (max. one day in between, 24 context repetitions per session).

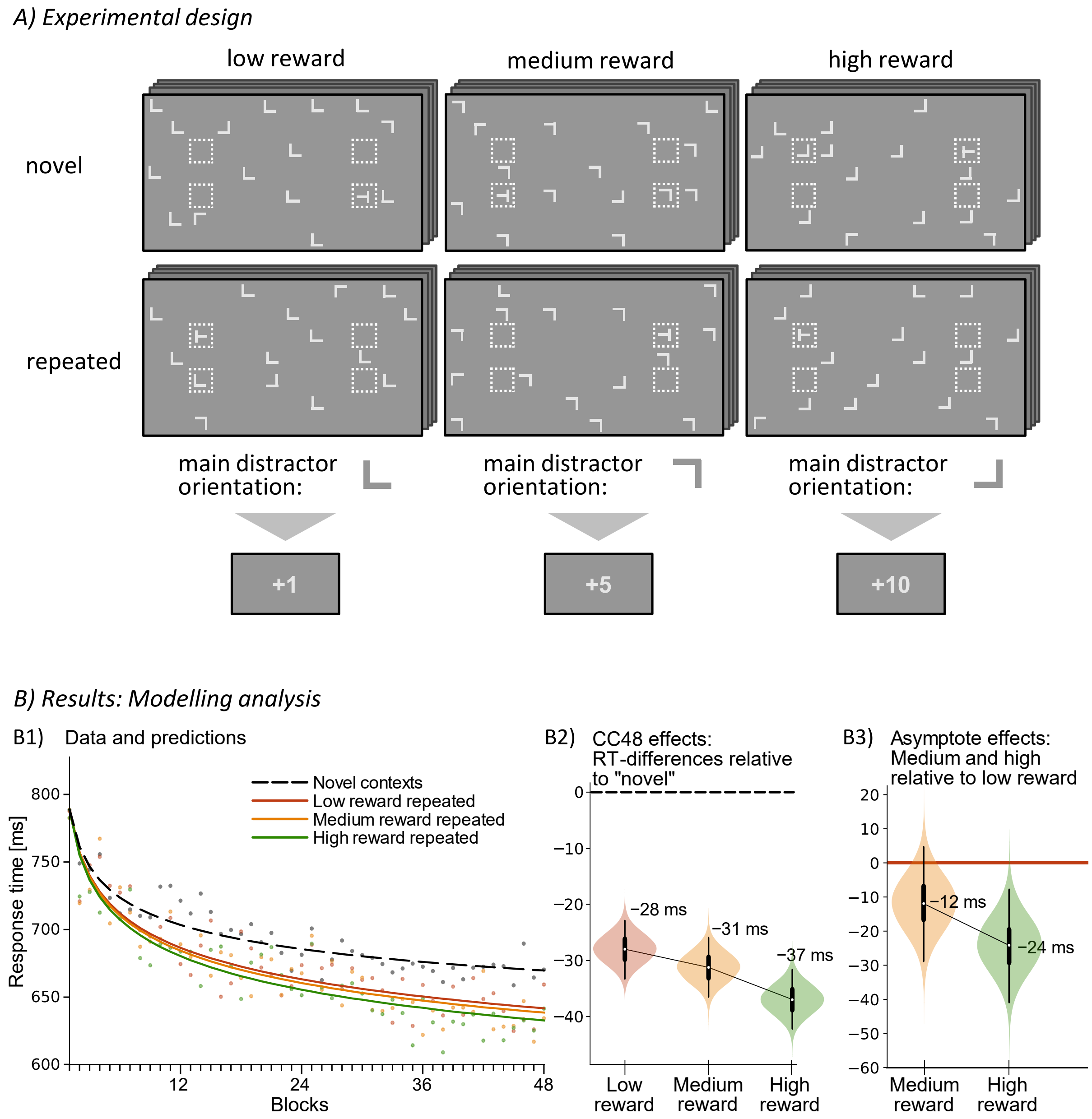

Fig. 3. (A) Experimental design of Study II and exemplary search contexts. As in Study I, participants performed a contextual cueing task with half of the distractor contexts repeating during the experiment. In each context, the predominant distractor orientation signaled either low, medium or high reward magnitude given for correct responses (association balanced across participants). The dotted boxes indicate potential target locations (not visible in the experiment). (B) Results of the modelling analysis. B1 shows the response time curves predicted by the model (lines), plotted with the means of the observed data in each in block (points). B2 depicts the estimated contextual cueing effect in block 48, separately for low, medium, and high reward contexts. B3 shows the influence of medium and high reward on the asymptotes of the repeated RT curves with low reward as a baseline (red line). Whiskers of the box-plots show the 95 % HPD interval, the thicker lines the 50 % HPD interval. The modes are marked with small white dots (values are plotted next to the distributions). (Figures reproduced from Bergmann, Tünnermann, & Schubö, 2020.)

To quantify behavioral performance and efficiency of attention guidance in novel and repeated contexts, we again examined response times and co-recorded eye movements (fixation count) in visual search. We observed faster responses and fewer fixations in repeated compared to novel contexts in contexts of all reward magnitudes, indicating that contextual cueing emerged in low, medium, and high reward contexts. In order to investigate whether a high reward persistently increased the CC effect, we applied a modelling analysis. This analysis quantified the shape of the RT curves by fitting a power function to the data, which was defined with a learning rate and an asymptotic performance parameter. We assumed that a persistent increase of CC would become visible in a decreased asymptote of the RT curves for repeated high reward contexts. Alternatively, an increased speed of learning with asymptotically similar performance, as Tseng and Lleras (2013) had reported, would be visible in a larger learning rate parameter.

The results of the parameter estimation of the model are shown in Fig. 3B. For novel contexts, reward affected neither the asymptotes nor the learning rate parameters of the curves. For repeated contexts, the model estimated that a high reward decreased the asymptotes of the curves (Fig. 3B, panel B3), whereas the learning rates were not affected. These results suggested that reward led to a persistent boost of contextual cueing rather than to earlier but asymptotically similar context configuration learning.

In sum, Study II extended the results of Study I by two important aspects. First, it demonstrated that associating reward with task-relevant context features could lead to boosts of the contextual cueing effect, as Study I had demonstrated for task-irrelevant features. It also replicated the finding that reward had no effects in novel contexts. Second, Study II confirmed that reward led to persistent boosts of contextual cueing, which manifested in decreased asymptotes of RTs in repeated contexts containing the reward-predicting context feature. The results of Study II thus suggest that reward-predicting features in the visual environment can have strong influences on how observers deal with repeating contextual information, even after many encounters.

2.3 Study III: Local and global context repetitions in contextual cueing

Reference

Bergmann, N., & Schubö, A. (in preparation). Local and global context repetitions in contextual cueing: The influence of reward.

Study summary

Studies I and II showed that task-relevant as well as irrelevant context features facilitated the learning of repeated contexts when they predicted reward. In both studies, the contexts either repeated entirely or were generated newly. In our natural environment, however, contexts can also repeat only in part, while other parts of the contexts are novel (cf. section 1.1.1). In contextual cueing, there is evidence for both, learning of global properties of the contexts, as well as learning of a restricted local context surrounding the target location (see Goujon et al., 2015, for a review).

Study III investigated whether observers could use global repeated and local repeated contexts for finding the target in a similar manner and whether reward-predicting context features facilitate the use of local and global contexts similarly. Since Studies I and II demonstrated that reward facilitates learning of global contexts, it seems likely that reward similarly facilitates learning of local contexts. On the other hand, it might also be possible that reward influences learning of global contexts more than local contexts because repeating only a restricted context might be not sufficient to focus attention near the target.

To investigate these alternatives, Study III used a modified version of the design of Study I. Participants performed a contextual cueing task with *three* context types (see Fig. 4A). In addition to the global repeated and novel contexts, which were also used in Study I, Study III included *local contexts*, in which only a patch surrounding the target repeated, while the remaining context configuration was generated randomly. The target patch contained three distractors and the target. Half of the context items in every context (local, global, and novel) were presented in color, the other half was gray. Color signaled either low or high reward, which participants could achieve when responding correctly. The target was colored in half of the contexts and the target patch always contained two colored and two gray items.

As in Studies I and II, we examined response times (see Fig. 4B) and fixation count to investigate how participants used local and global contexts for their search. In both local and global contexts, participants responded faster and made fewer fixations compared to novel contexts. Local contexts typically led to comparable benefits in response times and fixation count as global contexts did. Regarding reward, however, no differences where observed when comparing low and high reward contexts. Surprisingly, response times and fixation count were similar for low and high reward in novel, local, and global contexts.

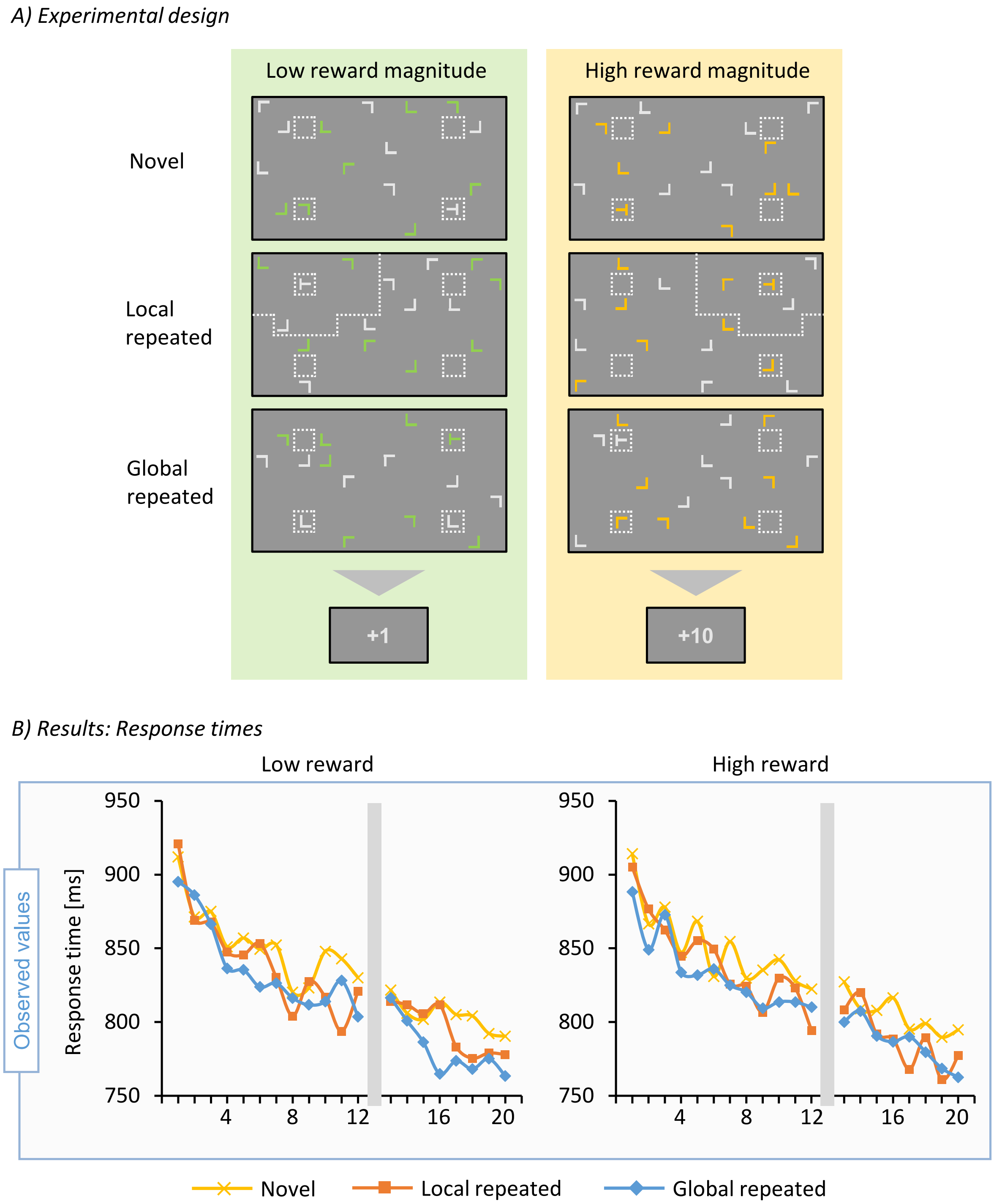

Fig. 4. (A) Experimental design and exemplary search contexts of Study III. Participants performed a contextual cueing task with three context types: Either the entire context repeated (global context), only a limited context surrounding the target repeated and the remaining context was novel (local context; indicated by the dotted lines, not visible in the experiment), or the entire context was novel (novel context). Half of the items in each context were colored, half were gray, and color predicted either low or high reward (association balanced across participants). The dotted boxes indicate potential target locations (not visible in the experiment). (B) Response times during the experiment, separately for low (left panel) and high reward (right panel). Novel contexts are shown as yellow, local as orange, global as blue lines. The gray bar depicts the gap (max. 1 day) between session 1 and 2. (Figures reproduced from Bergmann & Schubö, in preparation.)

When we examined response time differences between local and global contexts more closely, we observed a small local-global difference that seemed to depend on reward and target color. For low reward, local contexts had disadvantages compared to global contexts in the second session (see Fig. 4B, left panel), whereas there were no disadvantages for high reward. A comparison of response times for gray and colored targets revealed that this local-global difference was only visible for colored but not for gray targets. In addition, participants responded faster to gray than to colored targets in session 2, whereas response times did not differ in session 1.

We concluded that participants could use local and global contexts in a similar manner for detecting the target, manifesting in faster responses and fewer fixations to the target in local and global compared to novel contexts. At first glance, it seemed surprising that contextual cueing in local contexts was basically of similar size as in global contexts. In local contexts, only three distractors repeated, whereas in global contexts the entire search context repeated (15 distractors, see Fig. 4A). We concluded that the local contexts were searched as efficient as the global contexts because the target patch was large enough, covering approximately one quadrant of the screen (see Fig. 4A, cf. Brady & Chun, 2007), and because the random items always appeared outside the patch, which enabled to form reliable target-distractor associations within the patch (cf. Olson & Chun, 2002). In addition, we assumed that the ratio of local, global, and novel context trials facilitated context learning in the experiment. Two third of trials contained (at least a few) repeated items, which presumably contributed to contextual cueing in local and global contexts similarly (cf. Zinchenko, Conci, Müller, & Geyer, 2018).

In contrast to Study I, a high compared to low reward had no effect on contextual cueing in Study III, since we observed no differences when comparing novel, local, and global contexts with low and high reward. We concluded that the enclosure of the local contexts not only increased the proportion of trials with repeated items in the experiment, but also the absolute number of repeated contexts. Taken together, the number of local and global contexts was considerably larger than the number of repeated contexts in Studies I and II (Study I: 24 global contexts, Study II: 12 global contexts, Study III: 16 local and 16 global contexts). As a result, participants presumably had not enough learning resources left for learning the color-reward association in Study III, which could explain the lack of the reward effect. In line with this interpretation, only about one quarter of the participants reported that they recognized the color-reward association after the experiment. Thus, the lack of a reward effect in Study III does not necessarily contradict the findings of Studies I and II.

We also observed another difference compared to Study I. For session 2, we found that observers responded faster to contexts with gray compared to colored targets. In Study I, there were no differences between gray and colored targets. We concluded that resources for learning experimental regularities became available in session 2 and that observers tried to figure out the regularities of color, which might explain why they responded faster to gray than to colored targets in that session. This was especially crucial when processing the local contexts, since the display configuration of the local context patch contained only a very limited number of repeating context items (see Fig. 4A). Although speculative at this point, this could explain the small local-global difference observed for contexts with colored targets in session 2.

In sum, Study III adds to Studies I and II by demonstrating that observers are able to learn a very limited amount of repeated contextual information for guiding their search. Study III also found that participants adapted their search behavior to the target colors in the contexts, although this was neither helpful for finding the target on average, nor was such a behavior instructed. Study IV, which follows on the next page, directly adds to this finding by demonstrating how observers adapt their behavior to changing colors in the context.

2.4 Study IV: Observers dynamically adapt to changes in the visual context

Reference

Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on?: Adapting to color while searching for shape. *Attention, perception & psychophysics, 16*(3). https://doi.org/10.3758/s13414-019-01858-6

Study summary

Study IV examined the effects of a dynamically changing context on behavior in visual search (cf. section 1.1.2). To this end, it used a variant of the quite novel ACVS paradigm (Irons & Leber, 2016; see section 1.3.3) and examined another type of search behavior: the *choice* between two available targets.

Recent studies have shown that observers adapt their target choice to contextual changes in the target-defining feature dimension when they are free to choose between two available targets in visual search (Irons & Leber, 2016, 2018). In Study IV, we examined whether observers also adapt when the change occurs in a non-defining target dimension. Participants searched for a shape singleton target (diamond among circles) and were free to choose between two available targets in every trial (“free-choice task”). They responded by reporting a number shown inside the targets, and, as the numbers always differed between both targets, we could evaluate which target was chosen. In contrast to the contextual cueing experiments summarized above, the objects were (pseudo-)randomly placed on the screen in every trial. However, also in Study IV there was a regularity in the search contexts. The two targets always differed in color (gray vs. heterogeneous hues of blue in Exp. 1; blue vs. red in Exp. 2) and the ratio of distractors which were colored like each target changed in a predictable sequence in each experimental block. Fig. 5A depicts the trial sequence, exemplary for Exp. 2.

We hypothesized that participants would adapt their target preference to the color change by preferring the target from the smaller color subset. For evaluating the tendency to choose either target, we applied a modelling analysis. In this analysis, the tendency to select one of the two targets was modeled with a psychometric function. The slope of the function quantified the amount of adaptive choice (AC) behavior. The trial in the sequence where observers were equally likely to select both targets equaled the point of subjective equality (PSE). PSE estimates thus indicated where participants switched their target preference from one target to the other.

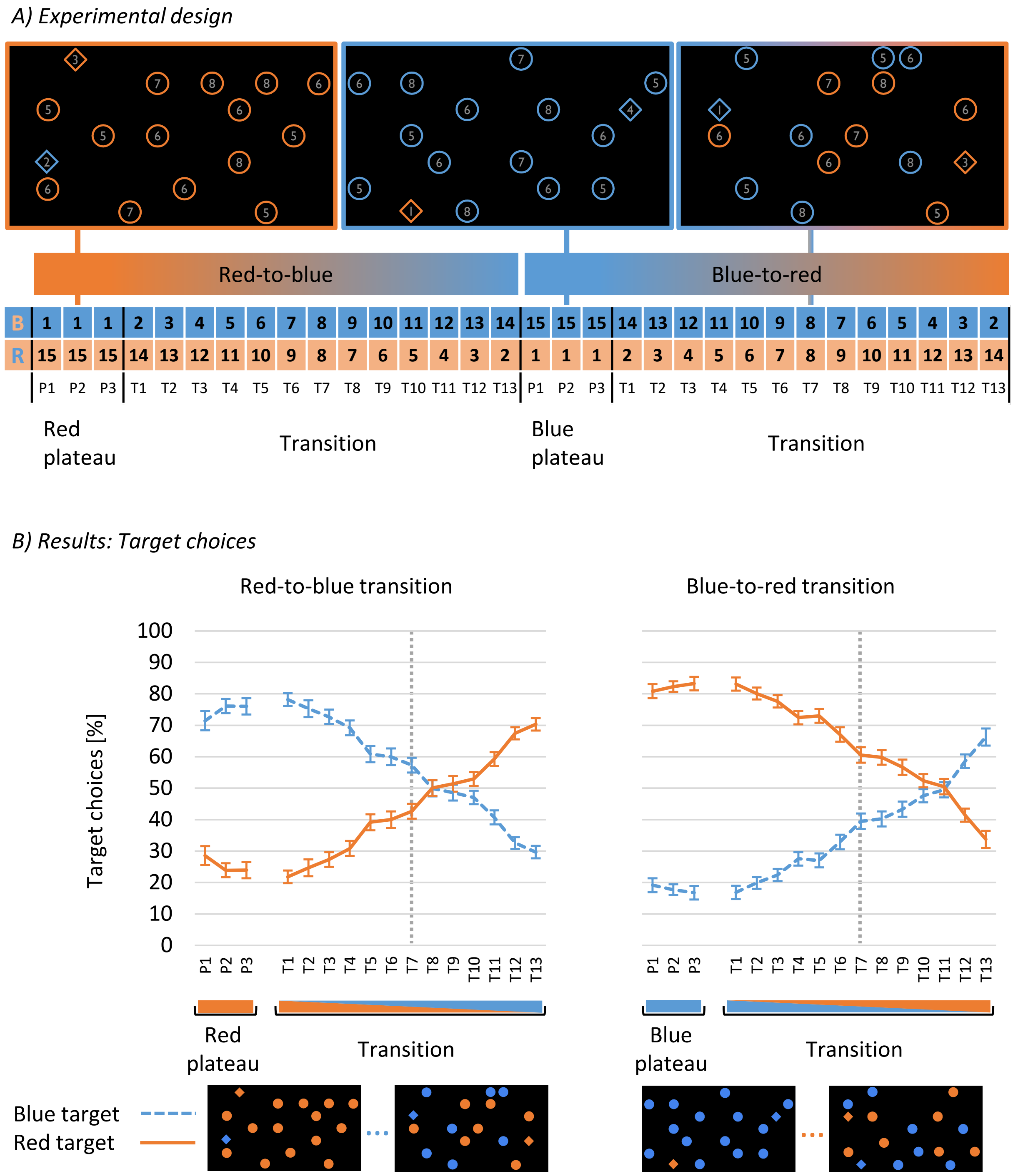

Fig. 5. (A) Exemplary search displays and trial sequence in a block of Study IV, Exp. 2. Participants reported the number inside one of the two diamond shape targets and were free to choose either target ("free-choice task"). One target was always blue, the other always red. The number of blue (row "B" in the table) and red distractors ("R") changed between red plateaus (all distractors in red) and blue plateaus (all distractors in blue). (B) Average target choices in Study IV (Exp. 2, "free-choice task") during the trial sequence. Dashed lines depict choices for blue, solid lines for red targets. The left panel depicts the red plateau and the red-to-blue transition, the right panel the blue plateau and the blue-to-red transition. Error bars show the standard error of the mean. (Figures reproduced from Bergmann, Tünnermann, & Schubö, 2019.)

Results confirmed that participants adapted their target choice to the trial sequence. They showed a tendency to choose the target whose color was less frequent in the context and they adapted their target choice towards preferring the other target when the ratio of the distractor colors changed during the trial sequence (Fig. 5B). Target choice adaptation (AC tendency) was more pronounced in Exp. 2, where participants could choose between subsets of homogeneous colors, compared to Exp. 1, where the items were gray and heterogeneously colored. The PSE estimates suggested that participants were slightly sluggish in adapting their target preference to the trial sequence. For both Experiments, the PSEs were estimated later than the objective point at which both color subsets were equally large (i.e., “T7”, cf. Fig. 5A).

As a control, we conducted two additional variants of the task, one in which participants were instructed about the trial sequence and advised to adapt their target choice (“informed-choice task”), and one in which the participants had to search for only one of the targets during the trial sequence (“forced-choice task”). These control conditions revealed that participants were able to show even more adaptation when explicitly instructed to adapt and that the difficulty to find one of the two targets increased with the number of distractors presented in similar colors.

We concluded that participants used color to search for targets although color was not a target-defining feature in the task, presumably because color was salient and therefore difficult to “ignore” during search. In addition, we concluded that target choice adaptation was more pronounced in Exp. 2 than in Exp. 1, because color homogeneity allowed for efficient element grouping without attentional resources (Duncan & Humphreys, 1989), fostering adaptation to the changing color ratio.

In sum, Study IV revealed that another type of search behavior, the choice between two targets, is influenced by the visual context. In addition to the results of Studies I-III, Study IV shows that dynamical *changes* of context features are registered and spontaneously integrated into behavior. Observers integrate dynamically changing contexts into their search behavior, even when they are irrelevant for the goal of the task. Such an adaptation is especially likely when changes can be processed easily and without attentional resources.

2.5 Study V: Individual differences in the context of social perception

Reference

Buchholz, M., Bergmann, N., Schubö, A., & Gollwitzer, M. (submitted). Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies.

Study summary

In contrast to Studies I-IV, Study V takes a different perspective on visual contexts by broadening the investigation of visual contexts to the disciplines of social and personality psychology. Study V primarily had two goals: First, it sought to examine how contexts of social perception influence the processing of congruent and incongruent visual stimuli. Second, it examined how the effects of the contexts were modulated by the observers' personality traits. To this end, the personality trait "victim sensitivity" was chosen as a promising candidate. There is evidence that, in contexts of social perception, victim sensitivity can bias memory of trustworthiness-related information (Süssenbach et al., 2016). Because of the well-established connection of visual attention to memory (e.g., Heuer & Schubö, 2018), we therefore hypothesized that victim sensitivity might also bias the allocation of visual attention towards trustworthiness-related visual information.

To investigate this possibility, a novel experimental paradigm was developed (Fig. 6A). Participants were confronted with the context of a face stimulus, which had either a trustworthy or an untrustworthy facial expression. After 2000 ms, the faces were accompanied by four words, which were either trustworthy, untrustworthy, or neutral (with regard to trustworthiness), visible for 3000 ms. Two main conditions were implemented. In the "trustworthy word condition", one word was trustworthy, while the remaining three words were neutral. In the "untrustworthy word condition", an untrustworthy word was shown together with three neutral words. For exploratory purposes, we also implemented a third condition in which one trustworthy and one untrustworthy word were presented in the same trial, accompanied by two neutral words (competition condition). In each experimental block, participants encountered trials of the three conditions in a randomized order. The face was constantly untrustworthy or trustworthy throughout a block but the facial expression varied across blocks.

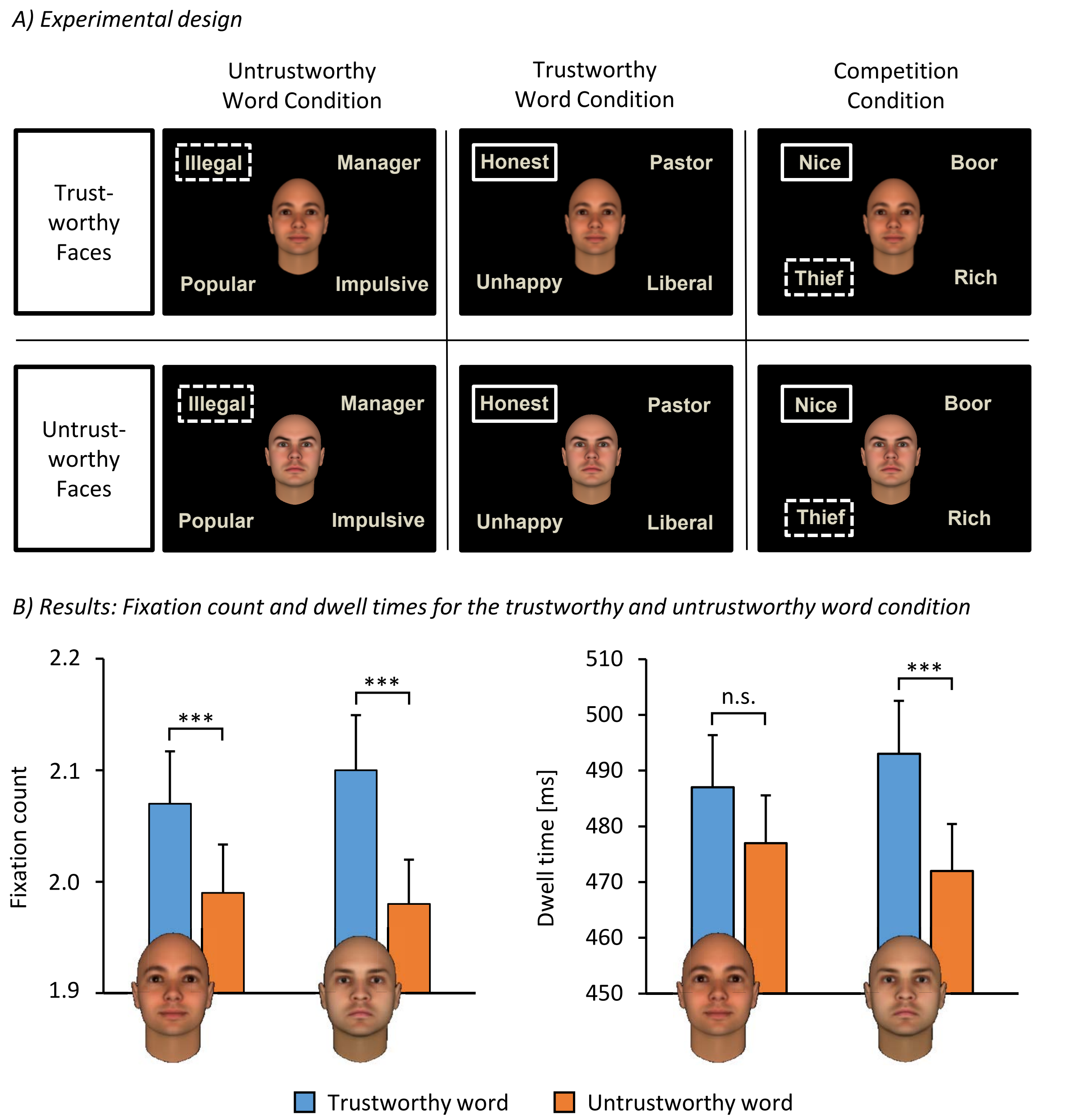

Fig. 6. (A) Experimental design of Study V. Participants were confronted with the context of a face stimulus presented at screen center. The face had either a trustworthy (upper row) or an untrustworthy facial expression (lower row). After 2000 ms, the faces were accompanied by four words, each presented in one quadrant of the screen for 3000 ms. The words were either trustworthy (indicated by the solid box), untrustworthy (dashed box), or neutral (no box). (B) Mean fixation count (left panel) and dwell times (right panel) for trustworthy contexts (left pairs of bars) and untrustworthy contexts (right pairs). Trustworthy words are shown in blue, untrustworthy words in orange. *** indicates that the difference is statistically significant ($p < .001$, two-tailed), n.s. that the difference is not significant. Error bars show the standard error of the mean. (Fig. A is reproduced from Buchholz, Bergmann, Schubö, & Gollwitzer, submitted. Fig. B depicts data that is shown in Table 1 of this manuscript. The faces were selected from two databases freely available to researchers conducting non-profit academic research; Original Computer Generated Faces, see Oosterhof & Todorov, 2008.)

We hypothesized that the contexts of the face stimuli would trigger expectations of (un)trustworthiness, which might bias subsequent visual processing of trustworthiness-related information. We suggested that incongruent stimuli, which violate the triggered expectation, might receive priority in the allocation of attention, since these stimuli might be most relevant for the observers. That is, when the face is untrustworthy, a trustworthy word might capture more attention than an untrustworthy word, and vice versa. Moreover, information that violates their negative expectations might be especially relevant to victim-sensitive individuals (Süssenbach et al., 2016). We therefore hypothesized that victim sensitivity might modulate the attention bias in the context of untrustworthy faces, with more victim-sensitive individuals showing more biases in their visual attention.

As a measure for visual attention allocation, we inspected the eye movement patterns of the participants. Separately for trustworthy and untrustworthy words, we examined the dwell time, fixation count, and the duration of the first fixation (see section 1.3.1). These measures were analyzed separately for trustworthy and untrustworthy contexts (i.e., faces; cf. Fig. 6A). In addition, we evaluated which of the words was fixated first in each trial. We assumed that a prioritization of attention allocation would manifest in longer dwell times, longer first fixation durations, more fixations, and an increased probability of the words being fixated first. To be able to compare these measures between the different words, we had to ensure that participants moved their eyes to all of the words in most of the trials. To this end, we used a cover story, instructing participants that they had to memorize the words of the last 5 trials, which successfully made them fixate most of the words in the experiment.

First, we analyzed the data of the "untrustworthy word" and the "trustworthy word" condition (cf. Fig. 6A). Results showed that in untrustworthy contexts, incongruent trustworthy words yielded increased dwell times and fixation count compared to congruent untrustworthy words (Fig. 6B, right pairs of bars). In trustworthy contexts, there was no significant difference in the dwell times. However, the (here congruent) trustworthy words were fixated more often than the incongruent untrustworthy words, although the difference was smaller than in untrustworthy contexts on a descriptive level[1]. There were no effects in the first fixation duration and in the words being fixated first. The competition condition (Fig. 6A, right column) was analyzed separately but could not replicate the results observed with the two main conditions. Presumably, this might be due to the fact that the words were assigned randomly to the quadrants. In some trials, the untrustworthy and the trustworthy word were presented on the same side of the screen, which might have caused interferences in the allocation of attention. Thus, the results of the competition condition might be difficult to interpret.

In a subsequent step, we examined whether victim sensitivity correlated with the differences between trustworthy and untrustworthy words, separately for trustworthy and

[1] Figure 6B visually suggests an interaction of word type and context type. However, the interaction effect missed statistical significance in the analysis.

untrustworthy contexts. Results showed that victim-sensitive individuals allocated more attention to words incongruent with untrustworthy contexts: Here, victim sensitivity was associated with longer first fixation durations for incongruent trustworthy words. In trustworthy contexts, victim-sensitive participants fixated incongruent untrustworthy words about equally long and often as congruent trustworthy words.

The results of Study V suggest that participants showed a bias for positive visual information, since they allocated more attention to trustworthy words compared to untrustworthy words in general (cf. Fig. 6B). Study V however also suggests that attention allocation was dependent on the contexts (i.e. the face stimuli). On a descriptive level, the attention bias towards trustworthy relative to untrustworthy words was increased for untrustworthy contexts. This might suggest that participants allocated increased attention to words that were incongruent with an untrustworthy context (cf. Fig. 6B). In addition, the influence of victim sensitivity also speaks in favor of context differences. Victim sensitivity was only associated with increased biases of visual attention allocation in untrustworthy but not in trustworthy contexts. This result also suggests that an individual's personality can modulate the effects of visual contexts on attention allocation.

In sum, Study V demonstrated that contexts of social perception bias the processing of congruent and incongruent visual information. Connecting visual contexts to the disciplines of social and personality psychology, Study V further shows that individual differences play an important role in how the contexts affect attention.

3 GENERAL DISCUSSION

This dissertation project studied how observers use visual contexts to guide their visual attention. In five studies, this dissertation examined three types of visual contexts: Repeated contexts which reappeared in part or in total, dynamically changing contexts which changed in a predictable sequence, and contexts of social perception which were used for studying individual differences in attention guidance.

The first and largest part of this dissertation investigated the effects of repeated contexts on attention guidance in visual search (Studies I-III), implementing variations of the contextual cueing paradigm (Chun & Jiang, 1998; see section 1.3.2). The results of Studies I-III demonstrated that observers exploit repeating context configurations to improve attention guidance in visual search. In all three studies, observers responded faster when the visual context repeated and, in all studies, this improvement went along with a reduced number of fixations during search. An increased search efficiency was not only observed when context configurations repeated entirely (Studies I and II), but also when only small parts of the contexts repeated (Study III). This dissertation contributes to a large number of studies in the contextual cueing literature (see Goujon et al., 2015; Sisk et al., 2019, for reviews) by investigating a new aspect of context learning: The influence of reward-predicting context features on the contextual cueing effect. The results show that reward-predicting colors (Study I) and distractor orientations (Study II) lead to persistent boosts of contextual cueing by facilitating the learning of repeated contexts. From a broad perspective, the first part of this dissertation therefore shows that stimuli signaling motivational value strengthen the use of repeated context configurations for guiding attention.

The second part of this dissertation examined how observers adapt their behavior to dynamically changing contexts in visual search (Study IV). To this end, a variation of the ACVS paradigm was used (Irons & Leber, 2016; see section 1.3.3), demonstrating that observers adapt their search behavior to changes in the contexts dynamically. The central novelty of Study IV was that observers adapted their behavior also when the change was implemented on an irrelevant feature dimension. That is, this dimension was per definition irrelevant when differentiating targets from distractors. By investigating the choice between two targets as dependent variable, Study IV could conclude that observers favored one target over another, dependent on the change in the visual contexts. The observed target choice adaptation suggests that observers adjusted their attention guidance to the change and that they adapted more strongly to homogeneous (Exp. 2) than to heterogeneous contexts (Exp. 1). Thus, the second part of this dissertation shows that observers not only integrate static repetitions of context configurations into their attention guidance but also adapt to predictable changes in the visual environment.

The third part of this dissertation was a cooperation project that broadened the view on visual contexts to the fields of social and personality psychology. To this end, a novel paradigm was developed, investigating contexts of social perception. In this paradigm, participants attended different words while being confronted with either trustworthy or untrustworthy contexts (face stimuli). The results showed that an observer's personality (i.e., victim sensitivity) modulated the influence of the contexts on attention allocation, and revealed that victim sensitivity strengthened the attentional bias towards incongruent words in untrustworthy contexts. The last part of this dissertation therefore shows that observers differ in how the contexts affect the allocation of their attention. Fig. 7 summarizes the main conclusions of the five studies of this dissertation.

	Main research question: ***How do observers use visual contexts to guide their attention?***		
	Studies I-III: Repeated contexts	**Study IV: Dynamically changing contexts**	**Study V: Contexts of social perception**
Research questions	How do observers exploit repeating contexts in their attention guidance? How do observers incorporate reward-predicting context features in the guidance of attention?	How do observers use dynamical changes in the visual context? How do observers adapt to irrelevant contextual regularities?	Study visual contexts with an interdisciplinary perspective: How does an observer's personality determine attention allocation in visual contexts?
Main conclusions	Observers use visual contexts to guide their attention when the context repeats entirely or in part. Context features predicting high reward persistently boost context learning. This holds for task-relevant and task-irrelevant features.	Observers adapt their behavior to dynamical changes in the visual context. They also adapt to changes which are implemented on an irrelevant feature dimension, especially in homogeneous contexts.	The observer's personality (victim sensitivity) modulates how incongruent information is processed in contexts of social perception. Observers differ in how they process visual contexts and personality might be one factor for explaining these differences.

Fig. 7. Research questions of this dissertation (introduced in Fig. 1), together with the main conclusions of the five studies. Three context types were examined: Repeated contexts (left column), dynamically changing contexts (middle column), and contexts of social perception (right column).

Taken together, the five studies of this dissertation demonstrate that observers are remarkably sensitive to regularities in their visual environment and use these regularities for allocating their visual attention. In what follows, the results of the five studies are discussed with regard to the theoretical concepts introduced in the introduction and connected to the existing literature. The first sections (sections 3.1 to 3.4) discuss the results of Studies I-IV, as they were the main focus of this dissertation and methodologically connected by applying visual search paradigms. Sections 3.5 and 3.6 then connect the results and conclusions of Studies I-IV to Study V.

3.1 Statistical learning

In Studies I-III, learning of repeated context configurations, i.e., contextual cueing, was observed. Contextual cueing is considered a statistical learning effect (Goujon et al., 2015): Observers learn that the target repeatedly appears at a certain location in a certain context and use this association when guiding attention to the target. The visual system exploits the repeating context configurations although observers are not instructed to use the contexts for finding the target, and although they are often not aware of the contexts repeating (but see Smyth & Shanks, 2008; Vadillo, Konstantinidis, & Shanks, 2016).

One might think that also the adaptation to the changing contexts observed in Study IV might be explainable by statistical learning (see Wang & Theeuwes, 2020). In the original ACVS paradigm, Irons and Leber (2016) instructed their participants about the color change in the contexts and implemented the change on a dimension that was target-defining (color was relevant for distinguishing targets from distractors). Based on the participants' reports after the experiment, the authors concluded that participants actively chose different strategies for using the change in their search behavior. In other words, participants selected different (top-down) attentional control settings. Study IV of the present dissertation made crucial changes to the original ACVS paradigm: Participants were not instructed to adapt (in the "free-choice task"), nor was the change implemented on a dimension relevant for distinguishing targets from distractors. However, participants still adapted their target choice to the contexts in Study IV. When they were asked to report their strategies after the experiment, only few participants reported to have actively used the color change for performing the task. In fact, the change actually went unnoticed by many participants. Thus, it appears that participants adapted spontaneously and presumably without explicit awareness to the change, suggesting that also the results of Study IV might be explainable by mechanisms of statistical learning.

3.1.1 Learning of locations

There is growing evidence that statistical learning can lead to biased processing of *locations*: Observers learn to prioritize locations associated with high probabilities of containing the target and avoid locations that are likely to contain distractors (e.g., Di Caro et al., 2019; Ferrante et al., 2018; Wang & Theeuwes, 2018a, 2018b, 2018c; see section 1.2.2). The contextual cueing experiments of this dissertation (Studies I-III) suggest that also repeated distractor contexts can lead to prioritized processing of locations in visual search. In Studies I-III, four target locations were used equally often during the experiments and the same locations were used in novel and repeated contexts. Therefore, all target locations were equally likely of containing a target during the experiments. Despite this fact, observers made fewer fixations to targets in repeated than in novel contexts, suggesting that guiding attention to the target location was facilitated by the contexts.

Geyer, Zehetleitner, and Müller (2010) suggested that in contextual cueing, observers use retrieved contextual information which they have acquired during the experiment to increase attentional weights at the target location on an overall salience-map. The highest activation on this map determines the allocation of attention and the selection of the target. The authors suggested that observers match the visual input in an upcoming trial with some form of context representation that they have stored in memory. After a bottom-up computation of salience signals, the pattern of position signals of the input is compared with stored position representations in memory. If the signals match a representation stored in memory, the attentional weights at the target location are increased. According to this notion, contextual cueing can thus be considered a statistical learning effect in which attentional weights on spatial locations are modulated.

At this point, one might argue that the increased efficiency of attention guidance to the target in repeated contexts might not necessarily be due to increased attentional weights at the target location. Alternatively, one might think that participants are generally better at *rejecting* a repeated context during search, as they have learned to reject the repeating distractors as "non-targets" more efficiently. Thus, one might argue that contextual cueing is actually due to a better rejection of known contexts than to a use of these contexts for guiding attention to the target location[2]. However, in their original paper, Chun and Jiang (1998) had observed that participants could not benefit from contexts in which the distractors repeated but the target changed its location (see also Beesley, Vadillo, Pearson, & Shanks, 2015). This suggests that participants use the contexts for guiding attention to relevant locations rather than learning to reject repeated contexts more efficiently.

3.1.2 Learning of features

In the contextual cueing experiment in Study III, we not only observed differences between novel and repeated contexts. Participants also responded faster to contexts with gray than with colored targets in the second session, an effect that was visible in repeated and in novel contexts. This result was surprising, because focusing on items in gray or color would be an inefficient strategy on average. One might speculate that participants perceived the target colors

[2] I would like to thank Leonardo Chelazzi for the fruitful discussions on this point.

as three different color categories (gray, orange, and green; cf. Fig. 4A). If so, the gray targets would be more frequent than green or orange targets in that experiment. Thus, one might think that participants adapted their search behavior to statistical regularities of *features* in the contexts of Study III, a behavior which might also be explainable by mechanisms of statistical learning (Cosman & Vecera, 2014; Failing et al., 2019). The results of Study IV directly add to this finding by showing that predictable changes of features can be integrated into an observer's search behavior. In Study IV, the participants dynamically changed their preference for either target dependent on the color ratio in the distractor contexts, which changed with each trial. Studies III and IV therefore suggests that statistical learning not only alters the processing of locations but also the prioritization of features in visual search.

In sum, Studies I-IV demonstrate that the visual context can bias processing of locations as well as features during visual search. They show that static regularities, like repeating distractor configurations, as well as dynamical changes are registered and integrated into behavior, processes presumably based on statistical learning.

3.2 The role of context homogeneity

Another point connecting Studies I-IV is the effect of context homogeneity. While Studies I and III examined contextual cueing using heterogeneous contexts in which the distractors were presented in various orientations, Study II used homogeneous contexts in which most distractors shared a common orientation. In the ACVS paradigm of Study IV, the contexts had homogeneous colors in Experiment 2 and heterogeneous colors in Experiment 1.

The role of context homogeneity for attention guidance in visual search was formulated in the *attentional engagement theory* by Duncan and Humphreys (1989). The authors assumed that distractor homogeneity was crucial for grouping processes at an early stage of visual processing. They proposed that a high distractor homogeneity led to efficient perceptual grouping, which allowed the visual system to process similar items as a single unit. As a result, the amount of visual information that had to be processed during visual search was reduced, which was beneficial for search efficiency. During the last centuries, many studies demonstrated that context homogeneity is indeed beneficial for search efficiency, as it fosters the deployment of attention by both, a facilitated detection of targets as well as rejection of distractors (Feldmann-Wüstefeld & Schubö, 2013; Schubö, Akyürek, Lin, & Vallines, 2011; Schubö, Wykowska, & Müller, 2007).

Context homogeneity is however not only reported to increase search efficiency in general. There is also evidence that context homogeneity increases the learning of repeated contexts observed with contextual cueing. Feldmann-Wüstefeld and Schubö (2014) conducted several contextual cueing experiments and varied context homogeneity on a task-relevant and a task-irrelevant dimension. The irrelevant dimension was color; contexts items were either presented in one, two, or four different colors. Color homogeneity affected neither search efficiency in general nor the size of contextual cueing. The task-relevant dimension was distractor orientation, which was relevant because participants had to determine the target orientation when responding (cf. the rationale of Study II in this dissertation, study summary in section 2.2). The authors used contexts with either one, two, or four distractor orientations. For the task-relevant orientation dimension, they found that visual search was facilitated in general by more homogeneous distractor orientations, observable as reduced response times in homogeneous compared to heterogeneous contexts. In addition, contextual cueing, measured as response time differences between repeated and novel contexts, was increased for homogeneous contexts. The authors concluded that context homogeneity helped perceptual grouping of the context items, which boosted not only search efficiency but also context learning.

3.2.1 Context homogeneity in Studies I-III

In the present dissertation, the contextual cueing experiments in Studies I and III used contexts with heterogeneous distractor orientations, whereas Study II used homogeneous orientations (80% of the distractors were presented in one orientation). In all studies, the contexts contained a similar number of context items (i.e., 16). When the response times of Studies II and III[3] are compared on a descriptive level, it is striking that the response times are generally faster in Study II compared to Study III (see Fig. 3B and 4B). It is very likely that this difference reflects the general homogeneity effect observed by Feldmann-Wüstefeld and Schubö (2014). Presumably, the homogeneous contexts in Study II were processed faster than the heterogeneous contexts in Study III because distractor homogeneity facilitated perceptual grouping of the context items (Duncan & Humphreys, 1989). However, it should be noted that context homogeneity also differed on the irrelevant "color" dimension across Studies II and III. Items were presented in two sets of colors in Study III (gray or colored) and were homogeneously gray in Study II. In addition, the target locations were placed at a slightly greater eccentricity in Study III compared to Study II, which complicates direct comparisons further. Nevertheless, it is very likely that the response time difference reflects an effect of distractor homogeneity.

Comparing the size of contextual cueing between Studies II and III is more difficult. The amount of context repetitions was larger in Study II than in Study III which would enable a larger contextual cueing effect in Study II compared to III. On the other side, Study III included not only global contexts repeating entirely but also local contexts, which repeated only in part. As a result, the ratio of repeated and novel context trials differed in that experiment: two third of trials contained repeating context items in Study III, only half of trials

[3] Study I used a smaller monitor than Studies II and III, making it difficult to compare response times of Studies I and II/III directly. The comparisons at this point are therefore limited to Studies II and III, which used the same monitor.

in Study II. This could have facilitated contextual cueing in Study III (see Zinchenko et al., 2018). However, it is likely that context homogeneity not only reduced response times in Study II but also facilitated contextual cueing.

3.2.2 Context homogeneity in Study IV

In Study IV, context homogeneity differed on a task-irrelevant feature dimension (i.e., color, see Krummenacher & Müller, 2012) across Experiments 1 and 2. In both experiments, participants were instructed to decide between one of two targets, which were defined as shape singletons (diamonds among circles). They indicated their chosen target by reporting a number, which was presented inside the targets. Thus, color was neither defining the target nor the correct response in Study IV. In Experiment 1, the context items were either gray or presented in different hues of blue. In Experiment 2, they were shown in homogeneous red or blue. Participants showed a much stronger tendency to adapt their target preference to the changing color ratio when the contexts were homogeneous (Experiment 2) compared to heterogeneous (Experiment 1). We concluded that homogeneity of the distractors allowed for spontaneous and effortless grouping of context items presented in similar colors. Presumably, using the changing color ratio for adapting target choice was therefore considerably less effortful in Experiment 2 compared to Experiment 1. As a result, context homogeneity fostered target choice adaptation.

The finding that homogeneity of the irrelevant color dimension affected search behavior in Study IV might imply that participants used color to search for targets, although color per se was “irrelevant”. The plateau trials of Study IV included trials, in which one of the targets was a salient color singleton (cf. Fig. 5A). Thus, participants might have been sensitized to using color for target search in Study IV. When participants used color to search for targets, color homogeneity may have also affected their search efficiency, with homogeneous contexts being searched more efficiently than heterogeneous contexts. This might also explain why Feldmann-Wüstefeld and Schubö (2014) observed no effect of color homogeneity in their contextual cueing study. Presumably, participants did not search using color in their experiment but searched for the target-defining T-junction. Therefore, color homogeneity had no effects in their study.

In sum, context homogeneity facilitated the exploitation of contextual regularities in the present dissertation. An increased context homogeneity enabled observers to adapt efficiently to the contexts, presumably because early perceptual grouping processes were facilitated. In Study II, these processes facilitated task performance in general. In Study IV, target choice adaptation was fostered.

3.3 Sleep facilitates context learning

Context homogeneity might not be the only factor that has fostered the effects of contexts in the present dissertation. A common feature of the contextual cueing studies (Studies I-III) is that all of these studies consisted of two separate sessions performed on separate days (with a maximum of one day in between). We divided the experiments into two sessions to keep each session short, so that participants would show less signs of fatigue during the experiments. However, one or two nights of sleep were between both sessions in these studies. Our participants usually reported to have slept about 7 hours on average in the night before session 2. Although investigating the effects of sleep was not the primary goal of these experiments, it is worth discussing how sleep influenced contextual cueing and the effects of reward in Studies I-III.

In a previous version of Study II, we originally included an additional analysis examining how contextual cueing changed between session 1 and 2[4]. We observed that the general level of response times and the contextual cueing effect were comparable at the end of session 1 (last 5 blocks) and the beginning of session 2 (first 5 blocks). However, we could also observe that that the fixation count was increased at the beginning of session 2 compared to the end of session 1. To answer how participants could maintain their performance level in responding in spite of making additional fixations, we analyzed the latency of the first saccade, that is, the time interval from stimulus onset until participants started the initiation of their first saccade. Results showed that the first saccade latencies were generally shorter at the beginning of session 2 compared to the end of session 1. We concluded that the faster initiation of the first saccade allowed for making more fixations, while maintaining a similar level of response times.

The shorter latencies observed at the beginning of the second session might be explainable by the role of sleep. There is evidence that sleep can enhance performance in texture discrimination tasks, which has been interpreted as facilitation of early visual discrimination abilities (Gais, Plihal, Wagner, & Born, 2000). According to this consideration, sleep might have facilitated early perceptual processes also in the contextual cueing studies of this dissertation. Since the task remained the same in both sessions, sleep might have enhanced discrimination and recognition of context configurations. This might explain the shorter first saccade latencies at the beginning of session 2. First saccade latency has been related to the speed of perceptual recognition in contextual cueing paradigms before (e.g., Zhao et al., 2012), and is considered to reflect initial perceptual processing of the contexts before the first saccade is initiated.

[4] Due to page limitations of the journal, this analysis was removed in the finally published revision of the article (Bergmann et al., 2020). Some of the following paragraphs were included in the General Discussion of the previous version of the manuscript. These parts were removed in the published article and are therefore published in this dissertation for the first time.

Moreover, sleep has also been considered to increase the size of contextual cueing, probably because it fosters consolidation of contextual information into long-term memory (Geyer, Müller, Assumpcao, & Gais, 2013). The authors conducted an experiment with two contextual cueing sessions on a single day, separated by either a short period of sleep (about 1 hour) or a controlled resting period. They found that sleep increased task performance in general and reduced response times in both repeated and novel contexts. Interestingly, the authors also observed an increased contextual cueing effect, that is, larger differences between repeated and novel contexts in the sleep group compared to the resting group. The authors concluded that sleep supported the consolidation of implicitly acquired contextual information, which increased the contextual cueing effect in session 2 (see also Born, Rasch, & Gais, 2006; Diekelmann & Born, 2010; Rasch & Born, 2013, for the role of sleep in memory consolidation). In the contextual cueing studies of the present dissertation, sleep might have been beneficial for contextual cueing, because it fostered consolidation of context learning from session 1.

One might speculate that sleep not only fostered contextual cueing in Studies I-III but also strengthened the effects of reward. Study II revealed that reward decreased the asymptotes of the repeated contexts' response time curve, that is, reward decreased response times towards the end of the experiment (session 2). One might therefore assume that sleep strengthens the association of the reward-predicting context features (color in Studies I and III, orientation in Study II) and the reward magnitude. Thus, sleep might have contributed to the contextual cueing advantages of high reward contexts observed in the present dissertation.

In sum, the sleep between both experimental sessions might have strengthened contextual cueing and the effects of reward in Studies I-III. However, it should be noted that the role of sleep was not the original scope of these experiments. Although the results suggest that sleep plays a role for contextual cueing and the effects of reward, it would need a control group without sleep to draw more certain conclusions (see Geyer et al., 2013).

3.4 Context and motivational value

The central novelty of the contextual cueing studies in this dissertation is that they introduced reward-predicting context features to the contextual cueing paradigm. In Studies I-III, participants received a reward for every correct response they gave within the response interval. The reward magnitude was low, medium, or high (low or high in Study III) and equaled a monetary bonus, granted after the experiment. Importantly, reward magnitude was not dependent on the participants' response speed. Fast and slow responses were followed by the same reward magnitude, as long as they were given within the response interval. However, reward magnitude was coupled to features of the search contexts, which were present in every trial; in particular, color in Studies I and III and distractor orientation in Study II. As soon as participants learned that a certain context feature was associated with a high or low reward, they could predict the reward magnitude with display onset.

We initially hypothesized that the prediction of a high reward would lead to a general increase in task performance (i.e., faster response times, fewer fixations), since participants might be especially motivated to perform the task when expecting to receive a high reward (e.g., Failing & Theeuwes, 2018). However, such an unspecific boost of task performance was observed in none of the three studies. Although this result was surprising for us at first, it might be easily explained by the fact that reward was not contingent on participants' response speed. Presumably, participants noticed that the reward magnitude was independent of their response times and only dependent on the context features. Therefore, they might have had no incentive to respond faster in high reward trials in general. However, we generally observed low error rates in Studies I-III, similarly for low and high reward. This might reflect that every correct response was rewarded with at least a low reward, whereas incorrect responses were not rewarded. Presumably, participants therefore had an incentive to answer correctly in every trial, which might have contributed to the low error rates.

3.4.1 Reward-predicting contexts are prioritized in context learning

While we observed no general boost of task performance in high reward contexts, high reward was beneficial to performance when the contexts repeated. We observed faster response times in repeated high compared to low reward contexts in Studies I and II. In both studies, reward did not affect response times in novel contexts. That is, reward facilitated learning of the repeated context configurations rather than leading to a general boost in task performance.

One might explain this result by assuming that the prediction of a high reward caused an increase in arousal, which presumably strengthened memory consolidation of the learned repeated contexts (cf. Eysenck, 1976; Tseng & Lleras, 2013). As a result, participants had stronger memory traces for high compared to low reward contexts, which facilitated using high reward repeated contexts for specifying the target location. This interpretation is supported by the more efficient eye movements to the target in high compared to low reward repeated contexts, which accompanied the faster responses in Studies I and II.

In addition, the results of Studies I and II suggest that high reward contexts received priority in context learning. There is evidence that observers have a limited capacity for context learning in contextual cueing (Schlagbauer, Müller, Zehetleitner, & Geyer, 2012), suggesting that participants are often not capable of learning all repeated contexts in contextual cueing experiments (but see Jiang, Song, & Rigas, 2005). The results of Study I speak in favor of such an interpretation: While we observed contextual cueing in high reward contexts, it was largely reduced or virtually absent in low and medium reward contexts. This finding suggests that observers allocated their limited learning resources to the high reward contexts (see also Pollmann et al., 2016).

Although contextual cueing was increased for high reward in Study II, we however observed contextual cueing for contexts of all reward magnitudes in that study. Moreover, the size of contextual cueing was comparable at the beginning of the experiment, as advantages of high reward contexts manifested on the asymptotes of the RT curves, i.e., towards the end of the experiment. Thus, it seems that participants had a stronger need to prioritize their learning resources in Study I compared to Study II. This can be explained by two important differences between the study designs of Study I and II. First, the number of repeated contexts in Study II was half as high as in Study I (12 vs. 24). Therefore, participants needed less capacity for the contexts of Study II compared to Study I. Second, the contexts of Study II were homogeneous in the used distractor orientations, whereas Study I used heterogeneous contexts (as outlined in section 3.2 in detail). One might think that context homogeneity further reduced the needed capacity for learning, presumably because grouping of the context items reduced the amount of information which had to be stored in memory (Duncan & Humphreys, 1989; Feldmann-Wüstefeld & Schubö, 2014). Thus, participants showed contextual cueing in contexts of all reward magnitudes in Study II because the contexts required less capacity.

In Study III, similar contextual cueing was observed for low and high reward contexts. Study III contained global repeated and local repeated contexts, in which only a patch around the target repeated. Thus, Study III included more individual repeated context configurations than Studies I and II, which would suggest that a prioritization of learning resources could be especially required in this study. However, since we observed no effect of reward, we concluded that participants did not learn to associate reward with features of the contexts, presumably because there were not enough learning resources left. It therefore seems that the enclosure of the local contexts was responsible for the absence of the reward effect in Study III, and that capacity limitations for learning experimental regularities might explain this result.

3.4.2 Reward speeds context processing

In the contextual cueing studies of the present dissertation, a high reward speeded response times in repeated contexts. The results discussed so far demonstrate that one reason for this advantage is an increased efficiency of attention guidance towards the target location (e.g., measured by fixation count). However, it seems that reward not only decreased response times by facilitating attention guidance to the target. As already mentioned in the previous section (3.3), we additionally analyzed saccadic latencies in a previous version of Study II[5]. In this analysis, we could also observe that participants initiated their first saccade fastest when the context feature (orientation) signaled a high reward, visible in both novel *and* repeated configurations.

[5] Some of the following paragraphs were included in the General Discussion of the previous version of the manuscript. These parts were removed in the published article and are therefore published in this dissertation for the first time.

To explain this result, we considered the assumptions of Geyer et al. (2010), outlined in section 3.1.1. The authors assumed that in contextual cueing, attentional weights are modulated after a comparison of visual input signals with some context representation in memory. We suggested that these comparison and weighting processes occur before participants initiate the first saccade to guide the eye toward the likely target location. This consideration receives support from studies reporting that first saccades land more frequently on the target in repeated than in novel contexts (e.g., Peterson & Kramer, 2001). We suggested that the expectation of high reward might facilitate this comparison process, for instance, because weights are higher than in low reward contexts, or because of a speeded weighting in general. Alternatively, reward expectation might speed the retrieval of contextual information. In either case, it seems that a high reward not only decreased response times because the eyes were guided more efficiently to the target location, but also because processing of the contexts was already speeded before the first saccade was initiated.

It should be noted that the influence of reward-predicting stimuli on saccadic latencies in visual search is not fully understood, i.e., not all studies find modulating effects of reward (Failing & Theeuwes, 2018). Nevertheless, the idea that reward facilitates matching encountered contextual information with representations in memory fits well to results from working memory studies. For instance, it was demonstrated that associating high reward with an object feature could increase the weight an object is assigned in a working memory task. In a change detection task (e.g., Heuer & Schubö, 2018), reward boosted memory performance by increasing an object's priority in encoding and in matching it to stored memory representations. In the light of these results it seems likely that also in the present dissertation, reward facilitated the matching of context representations stored in memory.

In sum, the present dissertation shows that repeated contexts signaling motivational value receive an increased priority in context learning and that memory for contextual information is especially acquired when context features signal a high reward.

3.5 Expectations and the visual context

In the previous sections, this discussion focused on the results of Studies I-IV. Study V differed to these studies, since it did not use a visual search task but implemented a newly developed experimental paradigm for studying visual contexts with an interdisciplinary perspective. It was assumed that presenting contexts of untrustworthy and trustworthy faces would trigger expectations of (un)trustworthiness, which might bias subsequent processing of trustworthiness-related visual information. This assumption was supported by the results, which showed that in untrustworthy contexts, incongruent trustworthy words (i.e., expectation violations) received an increased allocation of attention. In untrustworthy contexts, dwell times were larger for incongruent compared to congruent words, whereas dwell times did not differ significantly for trustworthy contexts (Fig. 6B). These results suggest that participants generated trustworthiness expectations based on the contexts, which biased processing of congruent and incongruent visual information during the upcoming trials of Study V.

Summerfield and de Lange (2014) suggested that observers use contextual information to generate expectations about future visual input which allows for a differential processing of expected compared to unexpected stimuli (see also Rief et al., 2015). The results of Study V might reflect such a differential processing, since in untrustworthy contexts, unexpected (i.e., incongruent) stimuli received priority compared to expected (i.e., congruent) stimuli in the allocation of visual attention. The theory of *predictive coding* (e.g., Friston, 2005; Rao & Ballard, 1999) suggests that an internal model of the world is used to generate predictions about expected outcomes. These predictions result from higher-order brain processes and are compared with lower sensory inputs (de Lange, Heilbron, & Kok, 2018; Rief et al., 2015). The theory assumes that the brain strives to minimize discrepancies between the internal model and the encountered sensory inputs. A *prediction error*, that is, a mismatch of the predictions of the internal model and the encountered sensory inputs, is crucial for updating the internal model and for the emergence of learning. In the light of this theory, it therefore makes sense for the brain to focus especially on information that is evaluated as prediction errors and it is assumed that attention plays a major role for this process by strengthening the error signal (Jiang, Summerfield, & Egner, 2013; Rief et al., 2015). This mechanism might explain why unexpected stimuli received priority in the allocation of attention in Study V: Unexpected stimuli represent a prediction error, and it is likely that these stimuli were therefore prioritized in the allocation of attention.

In Study V, we however observed differences not only between trustworthy and untrustworthy contexts but also found a “positivity bias”, that is, increased attention allocation towards trustworthy compared to untrustworthy words independent of the context. Gottlieb (2012) suggested that an organism uses attention to select information that is most relevant in the current situation. She described three distinct attentional mechanisms, which are each relevant for different aspects of behavior. The first mechanism “attention for action” describes that organisms pay attention to stimuli that are most relevant for an upcoming action. The second mechanism “attention for learning” posits that the visual system focuses especially on uncertain information in learning environments, as these stimuli are most relevant for reducing uncertainty. Gottlieb’s third mechanism “attention for liking” assumes that the organism attends to stimuli which are positive and signal a high reward. The mechanism “attention for liking” might explain the positivity bias observed in Study V. One might think that trustworthy information signals higher rewards (e.g., pleasant social interactions) compared to untrustworthy information, which could explain why participants prioritized trustworthy words in Study V – independent of expectations generated from the contexts.

Not only in Study V but also in Studies I-IV, participants could generate expectations about future visual input based on the visual contexts. In the contextual cueing experiments of

Studies I-III, participants could exploit the repeating contexts by learning an association of a repeated context and the embedded target location. This would allow observers to generate expectations about potential target locations when processing repeated contexts. However, such expectations were only possible in repeated contexts where the contexts predicted the target location, but could not be generated in novel contexts, which were unpredictive of the target location. The results of Study I speak in favor of this notion, since the first fixation landed closer to the target in repeated compared to novel contexts. Presumably, participants learned where to expect the target in repeated contexts, which allowed for a more precise direction of the first saccade. In line with this interpretation, there is recent evidence that contextual cueing has already begun to facilitate attention guidance at an early stage of the search process (Kobayashi & Ogawa, 2020). This suggests that the visual contexts in Studies I-III allowed to predict the target location early after stimulus onset.

With onset of the stimuli in Studies I-III, participants could also generate expectations about the reward magnitude they could achieve when responding correctly. This was possible because the reward-predicting context features allowed the prediction of a reward magnitude before the target was located. Previous studies demonstrated that the expectation of reward can increase oculomotor capture of single reward-predicting stimuli (e.g., Le Pelley, Pearson, Porter, Yee, & Luque, 2017). The present dissertation adds to these results by demonstrating how expectations of reward influence attention guidance when they are associated with features of an encountered context configuration rather than single stimuli. The results suggest that contexts predicting high reward are neither searched faster nor slower in general than context predicting low reward (cf. section 3.4). Instead, the expectation of reward was only beneficial to performance when the contexts repeated. This suggests that expectations of reward lead to facilitated processing of repeated contextual information.

While observers were able to generate expectations about target location and reward magnitude in Studies I-III, they could generate expectations about context features in Study IV. These expectations possibly affected participants' search, since there is evidence that expectations about features can bias subsequent behavior in visual tasks (Summerfield & de Lange, 2014; Summerfield & Egner, 2016). In Study IV, the contexts gradually changed their colors in a predictable sequence. Thus, participants could learn to expect how the color ratio changed during the upcoming trials and could anticipate how the colors would be composed in an upcoming context. One might speculate that these expectations allowed for a precise adaptation of target choice behavior to the trial sequence. Color homogeneity increased adaptive choice behavior in Experiment 2, which suggests that stimulus homogeneity fostered grouping of the context elements (see section 3.2.2). One might assume that grouping also allowed for a more precise detection of the change, which might in turn allow for generating more precise expectations about how the color ratio changed during the upcoming trials. Presumably, this allowed for a better planning of switching from one target to the other.

However, it would require a control experiment to make more certain conclusions about the role of expectations in Study IV. It would be interesting to evaluate whether presenting the contexts of Study IV in a randomized compared to a sequential order would impact the strength of adaptive choice behavior. If a random sequence of contexts weakened target choice adaptation compared to a fixed sequence, one might conclude that the generation of expectations is crucial for the adaptation of behavior.

In sum, the findings of the present dissertation suggest that the visual contexts allowed for the generation of expectations about future visual stimuli which biased the processing of upcoming visual information (de Lange et al., 2018; Summerfield & de Lange, 2014). The five studies of this dissertation focused on observers' behavior during the trial, measured by eye tracking and response times. These measures suggest that participants generated expectations during the experiments which biased their subsequent behavior. These findings would be a good starting point for future works, which could measure expectations more directly by investigating not only behavior during the trial but also the preparation for an upcoming trial, for instance, by using methods like EEG or fMRI (de Lange et al., 2018).

3.6 Inter-individual differences in context effects

Study V not only focused on examining the effects of trustworthiness expectations on visual processing in general, but also aimed at investigating individual differences in the effects of the visual context. The results show that an individual's personality can be an important factor for determining the influence of visual contexts. Observers scoring high on the personality trait "victim sensitivity" showed increased allocation of attention towards stimuli incongruent with untrustworthy contexts. This suggests that, in the contexts of social perception in Study V, victim sensitivity is modulating how strong the contexts bias attention, with people high on victim sensitivity showing more pronounced biases than people low on victim sensitivity.

The adaptive choice visual search paradigm, which was used in Study IV, was originally implemented to explore individual differences in an unconstrained visual context (Irons & Leber, 2016). Irons and Leber's paper concentrated on examining how observers differed in their adaptive choice behavior. By explicitly asking participants for their behavior after the experiment, the authors classified three groups of individuals: People who maximized performance by adapting, people who minimized effort by refraining from adapting, and people who randomly changed their behavior. When we asked participants for their behavior in Study IV, however, we could not observe the groups reported by Irons and Leber. Instead, many participants did not even notice that the colors were changing dynamically, which was especially pronounced for Experiment 1, where the color change was harder to recognize due to color heterogeneity.

While the self-reports did not reveal any distinct groups of participants, we however observed that individuals strongly differed in their adaptive choice behavior in Study IV.

Trying to determine potential factors which might explain this variation was difficult. We found a correlation of adaptive choice behavior and working memory capacity (measured as Corsi block span, Mueller & Piper, 2014), suggesting that observers with a larger capacity showed more adaptation than observers with a lower capacity. However, this correlation was only visible in one of the change directions and only in Experiment 1, while it was absent in Experiment 2. This could limit the informative value of this correlation. Thus, it remains unclear which individual dispositions might explain the variation of the context effects in Study IV.

Contextual cueing, which was used for examining repeated contexts in Studies I-III, is also an effect which was reported to show variability across individuals. For instance, there is evidence that some participants fail to show a contextual cueing effect during the experiment while others constantly show the effect, a difference which was suggested to be due to the implementation of differing search strategies (Lleras & Mühlenen, 2004). While individual differences were not of primary interest in Studies I-III, we however observed that only about one quarter of the participants recognized the color-reward association in Study III, while the association went unnoticed for the rest of the participants. In an exploratory analysis, which was not added to the final manuscript, we compared the group of "recognizers" with the rest of the participants. Interestingly, it seemed that the recognizers were primarily responsible for the small difference between low and high reward observed with the complete dataset in the second session. This might suggest that individual differences may also be important for the effects of reward and that the ability to (at least implicitly) recognize a reward-related association might be crucial.

In sum, the results of the present dissertation suggest that individuals vary in how the context affects their visual attention. While some individuals strongly use the contexts to guide their attention, others seem to implement differing strategies. This dissertation suggests that personality traits can be one factor for explaining these individual differences.

3.7 Perspectives for future research

While the five studies of the present dissertation showed that the visual context plays an important role for visual processing, they also raised new research questions which might be worth addressing in future research.

As was just discussed in the previous section, it might be interesting to investigate individual difference in the effects of contexts more closely. Study V demonstrated that personality could be one factor for explaining individual differences in contexts effects and Study IV suggested that individual abilities like working memory capacity may also play a role. It might be interesting to investigate more closely, which specific traits of the observers determine and modulate context effects.

Study II implemented a modelling approach for quantifying the response time curve of novel and repeated contexts in the contextual cueing paradigm. Future research might use this method and apply it to other research questions concerning contextual cueing. For instance, it would be interesting to compare the shape of the response time curves between the local and global contexts used in Study III. Although Study III suggests that learning of local and global contexts was mostly comparable, a future study could increase the number of context repetitions and examine whether this effect persists even after many context repetitions.

The persistence of the context effects observed in this dissertation could also be a research question for future work. Study II suggested that reward-predicting context features lead to a persistent increase of the contextual cueing effect. It would be worth testing how long this increase persists. One might think that high reward contexts show advantages even after a one-week break, since contextual cueing was reported to persist for such a time span (Chun & Jiang, 2003). However, it is also possible that the effects of reward are less persistent.

As was discussed in section 3.3, the results of the present dissertation suggest that sleep may have had beneficial influences on the effects of contexts. Future studies might work on the effects of sleep more profoundly. For instance, it could be interesting to evaluate whether sleep not only strengthens contextual cueing, as was reported previously (Geyer et al., 2013), but also strengthens the effects of reward. One might speculate that sleep strengthens the association of reward-predicting context features and a reward, which could increase the response time advantage of high reward repeated contexts.

4 CONCLUSION

In five studies, this dissertation expands our knowledge of how observers use visual contexts for guiding their attention. It shows that observers use repeated contexts that reappear entirely or in part for guiding attention to relevant locations, and that context features signaling motivational value strengthen this guidance effect. It further demonstrates that observers use not only static repetitions of context configurations in their search but also adapt to dynamical changes in the features of the context. In addition, this dissertation highlights that individuals differ considerably in how they use the contexts for allocating their attention and suggests personality as one factor for explaining these differences.

In sum, the present dissertation demonstrates that observers are remarkably sensitive to regularities in the visual context, and that they use the context for attention guidance when it helps them to structure their visual environment. In the light of the limited processing capacity of the visual system, the context therefore is an important source of information which helps us to quickly assess situations with an overload of visual information. Thus, the visual context is crucial for successfully managing numerous every-day situations.

5 REFERENCES

Albertella, L., Watson, P., Yücel, M., & Le Pelley, M. E. (2019). Persistence of value-modulated attentional capture is associated with risky alcohol use. *Addictive behaviors reports*, *10*, 100195. https://doi.org/10.1016/j.abrep.2019.100195

Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39. https://doi.org/10.1111/nyas.12957

Anderson, B. A., Laurent, P. A., & Yantis, S. (2013). Reward predictions bias attentional selection. *Frontiers in human neuroscience*, *7*, 262. https://doi.org/10.3389/fnhum.2013.00262

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

Beesley, T., Hanafi, G., Vadillo, M. A., Shanks, D. R., & Livesey, E. J. (2018). Overt attention in contextual cuing of visual search is driven by the attentional set, but not by the predictiveness of distractors. *Journal of experimental psychology. Learning, memory, and cognition*, *44*(5), 707–721. https://doi.org/10.1037/xlm0000467

Beesley, T., Pearson, D., & Le Pelley, M. (2019). Eye Tracking as a Tool for Examining Cognitive Processes. In *Biophysical Measurement in Experimental Social Science Research* (pp. 1–30). Elsevier. https://doi.org/10.1016/B978-0-12-813092-6.00002-2

Beesley, T., Vadillo, M. A., Pearson, D., & Shanks, D. R. (2015). Pre-exposure of repeated search configurations facilitates subsequent contextual cuing of visual search. *Journal of experimental psychology. Learning, memory, and cognition*, *41*(2), 348–362. https://doi.org/10.1037/xlm0000033

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of vision*, *19*(3), 1–18. https://doi.org/10.1167/19.3.10

Bergmann, N., & Schubö, A. (in preparation). Local and global context repetitions in contextual cueing: The influence of reward.

Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on?: Adapting to color while searching for shape. *Attention, perception & psychophysics*, *16*(3). https://doi.org/10.3758/s13414-019-01858-6

Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision research*, *171*, 53–63. https://doi.org/10.1016/j.visres.2020.03.010

Biederman, I., Mezzanotte, R. J., & Rabinowitz, J. C. (1982). Scene perception: Detecting and judging objects undergoing relational violations. *Cognitive psychology*, *14*(2), 143–177. https://doi.org/10.1016/0010-0285(82)90007-X

Born, J., Rasch, B., & Gais, S. (2006). Sleep to remember. *The Neuroscientist : a review journal bringing neurobiology, neurology and psychiatry*, *12*(5), 410–424. https://doi.org/10.1177/1073858406292647

Brady, T. F., & Chun, M. M. (2007). Spatial constraints on learning in visual search: modeling contextual cuing. *Journal of experimental psychology. Human perception and performance*, *33*(4), 798–815. https://doi.org/10.1037/0096-1523.33.4.798

Broadbent, D. E. (1958). *Perception and communication*. London: Pergamon Press.

Buchholz, M., Bergmann, N., Schubö, A., & Gollwitzer, M. (submitted). Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies.

Chelazzi, L., Perlato, A., Santandrea, E., & Della Libera, C. (2013). Rewards teach visual selective attention. *Vision research*, *85*, 58–72. https://doi.org/10.1016/j.visres.2012.12.005

Chun, M. M. (2000). Contextual cueing of visual attention. *Trends in Cognitive Sciences*, *4*(5), 170–178. https://doi.org/10.1016/S1364-6613(00)01476-5

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: implicit learning and memory of visual context guides spatial attention. *Cognitive psychology*, *36*(1), 28–71. https://doi.org/10.1006/cogp.1998.0681

Chun, M. M., & Jiang, Y. (2003). Implicit, long-term spatial contextual memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(2), 224–234. https://doi.org/10.1037/0278-7393.29.2.224

Cosman, J. D., & Vecera, S. P. (2014). Establishment of an attentional set via statistical learning. *Journal of experimental psychology. Human perception and performance*, *40*(1), 1–6. https://doi.org/10.1037/a0034489

de Lange, F. P., Heilbron, M., & Kok, P. (2018). How Do Expectations Shape Perception? *Trends in Cognitive Sciences*, *22*(9), 764–779. https://doi.org/10.1016/j.tics.2018.06.002

Deubel, H., & Schneider, W. X. (1996). Saccade target selection and object recognition: Evidence for a common attentional mechanism. *Vision research*, *36*(12), 1827–1837. https://doi.org/10.1016/0042-6989(95)00294-4

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

Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature reviews. Neuroscience*, *11*(2), 114–126. https://doi.org/10.1038/nrn2762

Driver, J. (2001). A selective review of selective attention research from the past century. *British Journal of Psychology*, *92*(1), 53–78. https://doi.org/10.1348/000712601162103

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. https://doi.org/10.1037/0033-295X.96.3.433

Engelmann, J. B., & Pessoa, L. (2007). Motivation sharpens exogenous spatial attention. *Emotion (Washington, D.C.)*, *7*(3), 668–674. https://doi.org/10.1037/1528-3542.7.3.668

Eysenck, M. W. (1976). Arousal, learning, and memory. *Psychological Bulletin*, *83*(3), 389–404. https://doi.org/10.1037/0033-2909.83.3.389

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

Failing, M., Nissens, T., Pearson, D., Le Pelley, M., & Theeuwes, J. (2015). Oculomotor capture by stimuli that signal the availability of reward. *Journal of neurophysiology*, *114*(4), 2316–2327. https://doi.org/10.1152/jn.00441.2015

Failing, M., & Theeuwes, J. (2017). Don't let it distract you: How information about the availability of reward affects attentional selection. *Attention, perception & psychophysics*, *79*(8), 2275–2298. https://doi.org/10.3758/s13414-017-1376-8

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. (2013). Context homogeneity facilitates both distractor inhibition and target enhancement. *Journal of vision*, *13*(3). https://doi.org/10.1167/13.3.11

Feldmann-Wüstefeld, T., & Schubö, A. (2014). Stimulus homogeneity enhances implicit learning: Evidence from contextual cueing. *Vision research*, *97*, 108–116. https://doi.org/10.1016/j.visres.2014.02.008

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; a journal devoted to the study of the nervous system and behavior*, *102*, 67–95. https://doi.org/10.1016/j.cortex.2017.09.027

Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1456), 815–836. https://doi.org/10.1098/rstb.2005.1622

Gais, S., Plihal, W., Wagner, U., & Born, J. (2000). Early sleep triggers memory for early visual discrimination skills. *Nature neuroscience*, *3*(12), 1335–1339. https://doi.org/10.1038/81881

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

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

Geyer, T., Müller, H. J., Assumpcao, L., & Gais, S. (2013). Sleep-effects on implicit and explicit memory in repeated visual search. *PloS ONE*, *8*(8), e69953. https://doi.org/10.1371/journal.pone.0069953

Geyer, T., Zehetleitner, M., & Müller, H. J. (2010). Contextual cueing of pop-out visual search: When context guides the deployment of attention. *Journal of vision*, *10*(5), 20. https://doi.org/10.1167/10.5.20

Gollwitzer, M., Rothmund, T., Alt, B., & Jekel, M. (2012). Victim sensitivity and the accuracy of social judgments. *Personality & social psychology bulletin*, *38*(8), 975–984. https://doi.org/10.1177/0146167212440887

Gollwitzer, M., Rothmund, T., & Süssenbach, P. (2013). The Sensitivity to Mean Intentions (SeMI) Model: Basic Assumptions, Recent Findings, and Potential Avenues for Future Research. *Social and Personality Psychology Compass*, *7*(7), 415–426. https://doi.org/10.1111/spc3.12041

Gottlieb, J. (2012). Attention, learning, and the value of information. *Neuron*, *76*(2), 281–295. https://doi.org/10.1016/j.neuron.2012.09.034

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Hansen, H. A., Irons, J. L., & Leber, A. B. (2019). Taking stock: The role of environmental appraisal in the strategic use of attentional control. *Attention, perception & psychophysics*. Advance online publication. https://doi.org/10.3758/s13414-019-01769-6

Harris, A. M., & Remington, R. W. (2017). Contextual cueing improves attentional guidance, even when guidance is supposedly optimal. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(5), 926–940. https://doi.org/10.1037/xhp0000394

Heuer, A., & Schubö, A. (2018). Separate and combined effects of action relevance and motivational value on visual working memory. *Journal of vision*, *18*(5), 14. https://doi.org/10.1167/18.5.14

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., Chelazzi, L., & Theeuwes, J. (2011). Reward has a residual impact on target selection in visual search, but not on the suppression of distractors. *Visual Cognition*, *19*(1), 117–128. https://doi.org/10.1080/13506285.2010.503946

Hickey, C., Chelazzi, L., & Theeuwes, J. (2014). Reward-priming of location in visual search. *PloS ONE*, *9*(7), e103372. https://doi.org/10.1371/journal.pone.0103372

Irons, J. L., & Leber, A. B. (2016). Choosing attentional control settings in a dynamically changing environment. *Attention, perception & psychophysics*, *78*(7), 2031–2048. https://doi.org/10.3758/s13414-016-1125-4

Irons, J. L., & Leber, A. B. (2018). Characterizing individual variation in the strategic use of attentional control. *Journal of experimental psychology. Human perception and performance*, *44*(10), 1637–1654. https://doi.org/10.1037/xhp0000560

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

Jiang, J., Summerfield, C., & Egner, T. (2013). Attention Sharpens the Distinction between Expected and Unexpected Percepts in the Visual Brain. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, *33*(47), 18438–18447. https://doi.org/10.1523/JNEUROSCI.3308-13.2013

Jiang, Y., & Leung, A. W. (2005). Implicit learning of ignored visual context. *Psychonomic bulletin & review*, *12*(1), 100–106. https://doi.org/10.3758/BF03196353

Jiang, Y., Song, J.-H., & Rigas, A. (2005). High-capacity spatial contextual memory. *Psychonomic bulletin & review*, *12*(3), 524–529. https://doi.org/10.3758/BF03193799

Jiang, Y. V., Swallow, K. M., Won, B.-Y., Cistera, J. D., & Rosenbaum, G. M. (2015). Task specificity of attention training: The case of probability cuing. *Attention, perception & psychophysics*, *77*(1), 50–66. https://doi.org/10.3758/s13414-014-0747-7

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

Kiss, M., Driver, J., & Eimer, M. (2009). Reward priority of visual target singletons modulates event-related potential signatures of attentional selection. *Psychological Science*, *20*(2), 245–251. https://doi.org/10.1111/j.1467-9280.2009.02281.x

Kobayashi, H., & Ogawa, H. (2020). Contextual cueing facilitation arises early in the time course of visual search: An investigation with the `speed-accuracy tradeoff task. *Attention, Perception, & Psychophysics*, *67*(19), 1. https://doi.org/10.3758/s13414-020-02028-9

Koenig, S., Kadel, H., Uengoer, M., Schubö, A., & Lachnit, H. (2017). Reward Draws the Eye, Uncertainty Holds the Eye: Associative Learning Modulates Distractor Interference in Visual Search. *Frontiers in behavioral neuroscience*, *11*, 128. https://doi.org/10.3389/fnbeh.2017.00128

Konstantopoulos, P., Chapman, P., & Crundall, D. (2010). Driver's visual attention as a function of driving experience and visibility. Using a driving simulator to explore drivers' eye movements in day, night and rain driving. *Accident; analysis and prevention*, *42*(3), 827–834. https://doi.org/10.1016/j.aap.2009.09.022

Krummenacher, J., & Müller, H. J. (2012). Dynamic weighting of feature dimensions in visual search: Behavioral and psychophysiological evidence. *Frontiers in psychology*, *3*, 221. https://doi.org/10.3389/fpsyg.2012.00221

Lavie, N., & Dalton, P. (2014). Load theory of attention and cognitive control. In A. C. Nobre & S. Kastner (Eds.), *The Oxford Handbook of Attention* (pp. 56–75). New York: Oxford Univ. Press.

Le Pelley, M. E., Mitchell, C. J., Beesley, T., George, D. N., & Wills, A. J. (2016). Attention and associative learning in humans: An integrative review. *Psychological Bulletin*, *142*(10), 1111–1140. https://doi.org/10.1037/bul0000064

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (2015). When goals conflict with values: counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of experimental psychology: General*, *144*(1), 158–171. https://doi.org/10.1037/xge0000037

Le Pelley, M. E., Pearson, D., Porter, A., Yee, H., & Luque, D. (2017). Oculomotor capture is influenced by expected reward value but (maybe) not predictiveness. *Quarterly journal of experimental psychology (2006)*, 1–46. https://doi.org/10.1080/17470218.2017.1313874

Le-Hoa Võ, M., & Wolfe, J. M. (2015). The role of memory for visual search in scenes. *Annals of the New York Academy of Sciences*, *1339*, 72–81. https://doi.org/10.1111/nyas.12667

Lleras, A., & Mühlenen, A. von. (2004). Spatial context and top-down strategies in visual search. *Spatial Vision*, *17*(4), 465–482. https://doi.org/10.1163/1568568041920113

Luck, S. J., & Hillyard, S. A. (1994). 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

Manginelli, A. A., Geringswald, F., & Pollmann, S. (2012). Visual Search Facilitation in Repeated Displays Depends on Visuospatial Working Memory. *Experimental Psychology*, *59*(1), 47–54. https://doi.org/10.1027/1618-3169/a000125

Mueller, S. T., & Piper, B. J. (2014). The Psychology Experiment Building Language (PEBL) and PEBL Test Battery. *Journal of neuroscience methods*, *222*, 250–259. https://doi.org/10.1016/j.jneumeth.2013.10.024

Olson, I. R., & Chun, M. M. (2002). Perceptual constraints on implicit learning of spatial context. *Visual Cognition*, *9*(3), 273–302. https://doi.org/10.1080/13506280042000162

Oosterhof, N. N., & Todorov, A. (2008). The functional basis of face evaluation. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(32), 11087–11092. https://doi.org/10.1073/pnas.0805664105

Palmer, T. E. (1975). The effects of contextual scenes on the identification of objects. *Memory & Cognition*, *3*(5), 519–526. https://doi.org/10.3758/BF03197524

Peterson, M. S., & Kramer, A. F. (2001). Attentional guidance of the eyes by contextual information and abrupt onsets. *Perception & Psychophysics*, *63*(7), 1239–1249. https://doi.org/10.3758/BF03194537

Pollmann, S., Eštočinová, J., Sommer, S., Chelazzi, L., & Zinke, W. (2016). Neural structures involved in visual search guidance by reward-enhanced contextual cueing of the target location. *NeuroImage*, *124*(Pt A), 887–897. https://doi.org/10.1016/j.neuroimage.2015.09.040

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

Posner, M. I. (2016). Orienting of attention: Then and now. *Quarterly journal of experimental psychology (2006)*, *69*(10), 1864–1875. https://doi.org/10.1080/17470218.2014.937446

Rao, R. P. N., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature neuroscience*, *2*(1), 79–87. https://doi.org/10.1038/4580

Rasch, B., & Born, J. (2013). About sleep's role in memory. *Physiological reviews*, *93*(2), 681–766. https://doi.org/10.1152/physrev.00032.2012

Rief, W., Glombiewski, J. A., Gollwitzer, M., Schubö, A., Schwarting, R., & Thorwart, A. (2015). Expectancies as core features of mental disorders. *Current opinion in psychiatry*, *28*(5), 378–385. https://doi.org/10.1097/YCO.0000000000000184

Said, C. P., Dotsch, R., & Todorov, A. (2010). The amygdala and FFA track both social and non-social face dimensions. *Neuropsychologia*, *48*(12), 3596–3605. https://doi.org/10.1016/j.neuropsychologia.2010.08.009

Schankin, A., & Schubö, A. (2009). Cognitive processes facilitated by contextual cueing: Evidence from event-related brain potentials. *Psychophysiology*, *46*(3), 668–679. https://doi.org/10.1111/j.1469-8986.2009.00807.x

Schankin, A., & Schubö, A. (2010). Contextual cueing effects despite spatially cued target locations. *Psychophysiology*, *47*(4), 717–727. https://doi.org/10.1111/j.1469-8986.2010.00979.x

Schlagbauer, B., Geyer, T., Müller, H. J., & Zehetleitner, M. (2014). Rewarding distractor context versus rewarding target location: a commentary on Tseng and Lleras (2013). *Attention, perception & psychophysics*, *76*(3), 669–674. https://doi.org/10.3758/s13414-014-0668-5

Schlagbauer, B., Müller, H. J., Zehetleitner, M., & Geyer, T. (2012). Awareness in contextual cueing of visual search as measured with concurrent access- and phenomenal-consciousness tasks. *Journal of vision*, *12*(11), 1–12. https://doi.org/10.1167/12.11.25

Schubö, A., Akyürek, E. G., Lin, E.-J., & Vallines, I. (2011). Cortical mechanisms of visual context processing in singleton search. *Neuroscience Letters*, *502*(1), 46–51. https://doi.org/10.1016/j.neulet.2011.07.022

Schubö, A., Wykowska, A., & Müller, H. J. (2007). Detecting pop-out targets in contexts of varying homogeneity: Investigating homogeneity coding with event-related brain potentials (ERPs). *Brain research*, *1138*, 136–147. https://doi.org/10.1016/j.brainres.2006.12.059

Sharifian, F., Contier, O., Preuschhof, C., & Pollmann, S. (2017). Reward modulation of contextual cueing: Repeated context overshadows repeated target location. *Attention, perception & psychophysics*. (79), 1871–1877. https://doi.org/10.3758/s13414-017-1397-3

Sisk, C. A., Remington, R. W., & Jiang, Y. V. (2019). Mechanisms of contextual cueing: A tutorial review. *Attention, perception & psychophysics*, *81*(8), 2571–2589. https://doi.org/10.3758/s13414-019-01832-2

Smyth, A. C., & Shanks, D. R. (2008). Awareness in contextual cuing with extended and concurrent explicit tests. *Memory & Cognition*, *36*(2), 403–415. https://doi.org/10.3758/MC.36.2.403

Song, J.-H., & Jiang, Y. (2005). Connecting the past with the present: How do humans match an incoming visual display with visual memory? *Journal of vision*, *5*(4), 322–330. https://doi.org/10.1167/5.4.4

Stilwell, B. T., Bahle, B., & Vecera, S. P. (2019). Feature-based statistical regularities of distractors modulate attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(3), 419–433. https://doi.org/10.1037/xhp0000613

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., & Egner, T. (2016). Feature-Based Attention and Feature-Based Expectation. *Trends in Cognitive Sciences*, *20*(6), 401–404. https://doi.org/10.1016/j.tics.2016.03.008

Süssenbach, P., Gollwitzer, M., Mieth, L., Buchner, A., & Bell, R. (2016). Trustworthy Tricksters: Violating a Negative Social Expectation Affects Source Memory and Person Perception When Fear of Exploitation Is High. *Frontiers in psychology*, *7*, 2037. https://doi.org/10.3389/fpsyg.2016.02037

Theeuwes, J. (2018). Visual Selection: Usually Fast and Automatic; Seldom Slow and Volitional. *Journal of Cognition*, *1*(1), 67. 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. https://doi.org/10.1016/j.copsyc.2018.12.024

Treisman, A. (1988). Features and objects: The fourteenth bartlett memorial lecture. *The Quarterly Journal of Experimental Psychology Section A*, *40*(2), 201–237. https://doi.org/10.1080/02724988843000104

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

Tseng, Y.-C., & Li, C.-S. R. (2004). Oculomotor correlates of context-guided learning in visual search. *Perception & Psychophysics*, *66*(8), 1363–1378. https://doi.org/10.3758/BF03195004

Tseng, Y.-C., & Lleras, A. (2013). Rewarding context accelerates implicit guidance in visual search. *Attention, perception & psychophysics*, *75*(2), 287–298. https://doi.org/10.3758/s13414-012-0400-2

Vadillo, M. A., Konstantinidis, E., & Shanks, D. R. (2016). Underpowered samples, false negatives, and unconscious learning. *Psychonomic bulletin & review*, *23*(1), 87–102. https://doi.org/10.3758/s13423-015-0892-6

Võ, M. L.-H., Boettcher, S. E., & Draschkow, D. (2019). Reading scenes: How scene grammar guides attention and aids perception in real-world environments. *Current opinion in psychology*, *29*, 205–210. https://doi.org/10.1016/j.copsyc.2019.03.009

Wang, B., & Theeuwes, J. (2018a). 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., & Theeuwes, J. (2018b). 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. (2018c). Statistical regularities modulate attentional capture independent of search strategy. *Attention, perception & psychophysics*, *80*(7), 1763–1774. https://doi.org/10.3758/s13414-018-1562-3

Wang, B., & Theeuwes, J. (2020). Implicit attentional biases in a changing environment. *Acta Psychologica*, *206*, 103064. https://doi.org/10.1016/j.actpsy.2020.103064

Wolfe, J. M. (1994). Guided Search 2.0 A revised model of visual search. *Psychonomic bulletin & review*, *1*(2), 202–238. https://doi.org/10.3758/BF03200774

Wolfe, J. M. (2014). Approaches to visual search: Feature integration theory and guided search. In A. C. Nobre & S. Kastner (Eds.), *The Oxford Handbook of Attention* (pp. 11–55). New York: Oxford Univ. Press.

Wolfe, J. M. (2020a). Forty years after feature integration theory: An introduction to the special issue in honor of the contributions of Anne Treisman. *Attention, perception & psychophysics*, *82*(1), 1–6. https://doi.org/10.3758/s13414-019-01966-3

Wolfe, J. M. (2020b). Major issues in the study of visual search: Part 2 of "40 Years of Feature Integration: Special Issue in Memory of Anne Treisman". *Attention, perception & psychophysics.* Advance online publication. https://doi.org/10.3758/s13414-020-02022-1

Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *15*(3), 419–433. https://doi.org/10.1037/0096-1523.15.3.419

Won, B.-Y., Kosoyan, M., & Geng, J. J. (2019). Evidence for second-order singleton suppression based on probabilistic expectations. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(1), 125–138. https://doi.org/10.1037/xhp0000594

Yarbus, A. L. (1967). *Eye Movements and Vision*. New York: Plenum Press.

Zhao, G., Liu, Q., Jiao, J., Zhou, P., Li, H., & Sun, H.-j. (2012). Dual-state modulation of the contextual cueing effect: Evidence from eye movement recordings. *Journal of vision*, *12*(6), 1–13. https://doi.org/10.1167/12.6.11

Zinchenko, A., Conci, M., Müller, H. J., & Geyer, T. (2018). Predictive visual search: Role of environmental regularities in the learning of context cues. *Attention, perception & psychophysics*, *80*(5), 1096–1109. https://doi.org/10.3758/s13414-018-1500-4

ORIGINAL MANUSCRIPTS

In the following sections, the original manuscripts of this thesis, summarized in section 2, are included. Respecting the journals' copyrights, the final published versions of the articles are used (when available), as they are permitted to be included in a dissertation. The reader is referred to the original sources of the articles with the following references:

Study I (pages 67 – 84)
Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision, 19*(3), 1–18. https://doi.org/10.1167/19.3.10

Study II (pages 85 – 95)
Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision Research, 171*, 53–63. https://doi.org/10.1016/j.visres.2020.03.010

Study III (pages 96 – 121)
Bergmann, N., & Schubö, A. (in preparation). Local and global context repetitions in contextual cueing: The influence of reward.

Study IV (pages 122 – 142)
Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on?: Adapting to color while searching for shape. *Attention, perception & psychophysics, 16*(3). https://doi.org/10.3758/s13414-019-01858-6

Study V (pages 143 – 172)
Buchholz, M., Bergmann, N., Schubö, A., & Gollwitzer, M. (submitted). Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies.

Study I

Journal of Vision (2019) 19(3):10, 1–18 1

Reward expectation facilitates context learning and attentional guidance in visual search

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Modulations of visual attention due to expectation of reward were frequently reported in recent years. Recent studies revealed that reward can modulate the implicit learning of repeated context configurations (e.g., Tseng & Lleras, 2013). We investigated the influence of reward expectations on context learning by associating colors to different reward magnitudes. Participants searched through contexts consisting of spatially distributed L-shaped distractors and a T-shaped target, with half of these objects appearing in a color associated with low, medium, or high reward. Half of these context configurations were repeatedly presented in every experimental block, whereas the other half was generated newly for every trial. Results showed an earlier and more pronounced contextual cueing effect in contexts associated with high reward compared with low reward contexts. This was visible as faster decline of response times to targets in repeated contexts associated with high reward compared with repeated low reward and novel contexts, and was reflected in the eye movement pattern as shorter distance of the first fixation to the target location. These results suggest that expectation of high reward magnitude facilitates subsequent learning of repeated context configurations. High reward also increases the efficiency of attention guidance toward the target location.

Introduction

Humans are consistently confronted with changing environments containing new and possibly unknown information. To ensure successful adaption of subsequent behavior, humans have to select relevant information relying on information sampling from their visual environment. Due to the limited processing capacity, relevant situational features might be missed if priority is given to nonrelevant features (Simons & Levin, 1997). Therefore, visual information has to be prioritized for attentional selection (Driver, 2001; Lavie & Dalton, 2014).

Reward influencing attention guidance

Associated rewards have been proven powerful in prioritizing visual information processing, as formerly experienced extrinsic (e.g., monetary) rewards were reported to have a huge influence on human selective attention (Della Libera & Chelazzi, 2006, 2009; for reviews, see Anderson, 2016; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Failing & Theeuwes, 2018). Reward-induced selection biases were even observed to overrule an observer's intention (Feldmann-Wüstefeld, Brandhofer, & Schubö, 2016; Hickey & van Zoest, 2013; Le Pelley, Pearson, Griffiths, & Beesley, 2015; Le Pelley, Seabrooke, Kennedy, Pearson, & Most, 2017) as well as a stimulus' salience (Anderson, 2016; Chelazzi et al., 2013; Hickey, Chelazzi, & Theeuwes, 2010). As Awh and colleagues pointed out, these findings cannot be explained by referring to the classical dichotomy between top-down and bottom-up processes in attention guidance (Awh, Belopolsky, & Theeuwes, 2012).

Several studies have demonstrated that formerly rewarded target locations and locations that were

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associated with higher probabilities of reward are prioritized in attentional selection in visual search tasks (Anderson, 2013; Hickey et al., 2010; Hickey, Chelazzi, & Theeuwes, 2011). Hickey et al. (2010), for instance, asked participants to search for a singleton shape target in a visual search task and to ignore an additional singleton distractor presented in a deviating color. A high or low reward was randomly given after each correct trial. In any given pair of successive trials, the target and distractor colors could either be maintained or swapped, yet color was entirely irrelevant for the task. Results showed that reward magnitude in trial n–1 affected search performance in trial n: High reward in trial n–1 led to shorter response times in trial n when colors were repeated compared with color change trials. Conversely, low reward in trial n–1 resulted in longer response times in trial n when colors were repeated compared with color change trials. These results indicate that associating a specific feature with reward can result in immediate prioritization of that feature in subsequent trials. Subsequent experiments showed that also specific locations in visual search tasks can be prioritized by reward outcome (Hickey, Chelazzi, & Theeuwes, 2014): A high reward in trial n–1 not only facilitated the return of attention to the same target location in trial n but also inhibited the deployment of attention to a location that held a salient irrelevant distractor in trial n–1. Thus reward seems to guide attentional selection by priming particular locations of visual stimuli (Hickey et al., 2014). Important to note, this "location priming" is not based on the observers' voluntary or strategic decision, but rather results from the association of a location with a previous reward outcome (Awh et al., 2012).

Eye movement studies have also shown that the presence of reward-signaling stimuli can bias attention and result in oculomotor capture (e.g., Hickey & van Zoest, 2013), even when the stimulus is not relevant but even counterproductive for the actual task (Failing, Nissens, Pearson, Le Pelley, & Theeuwes, 2015; Le Pelley et al., 2015). The presence of a distractor signaling reward was also found to lead to saccades landing closer to high reward distractors (Bucker, Belopolsky, & Theeuwes, 2014) and to increased saccade latencies to the target (Le Pelley et al., 2015). These results provide further evidence that reward can bias attentional selection to those locations and object features that signal subsequent reward. Such prioritizations in attention guidance can work automatically and against an observer's intention. Depending on the actual goal of the task, these reward influences on attention guidance can have beneficial or counterproductive effects on task performance (cf. Le Pelley et al., 2015).

Attention guidance in contextual cueing

Not only formerly experienced rewards but also recurrent contextual regularities can result in facilitated processing of visual information (Summerfield & de Lange, 2014). Statistical learning mechanisms can help the observer to detect contextual regularities in visual search and to localize the target (Goujon, Didierjean, & Thorpe, 2015). Studies investigating the influence of spatial contextual regularities often used contextual cueing tasks (Chun & Jiang, 1998) in which participants performed a visual search task searching for one target among a spatial configuration of distractors (Chun, 2000; Chun & Turk-Browne, 2007; Goujon et al., 2015; Le-Hoa Võ & Wolfe, 2015). In each experimental block, half of these configurations were repeatedly presented ("repeated contexts") and presented randomly intermixed with configurations newly generated for each trial ("novel contexts"). During the experiment, participants became faster in responding to the target when searching through repeated relative to novel contexts, an advantage that was also reflected in accuracy measures in some studies (Feldmann-Wüstefeld & Schubö, 2014; Pollmann, Eštočinová, Sommer, Chelazzi, & Zinke, 2016; Sharifian, Contier, Preuschhof, & Pollmann, 2017). Better search performance for repeated compared with novel contexts typically became apparent after six repetitions and reached an asymptote after 10 to 30 exposures to repeated contexts (Chun & Jiang, 1998, 1999, 2003; Feldmann-Wüstefeld & Schubö, 2014; Olson & Chun, 2001; van Asselen & Castelo-Branco, 2009). The effect seems to be relatively stable in time, as differences between context types were still observed after one week (Jiang, Song, & Rigas, 2005; Zellin, Mühlenen, Müller, & Conci, 2014).

One prominent explanation of the contextual cueing effect claims that context knowledge that is acquired during context repetition facilitates attention guidance (Goujon et al., 2015; Harris & Remington, 2017). Accordingly, repeated context configurations were considered to function as cues that guide attention toward the expected target location (Chun & Jiang, 1998). In line with this, repeated contexts were observed to be associated with an increased N2pc component in electroencephalography studies (Schankin, Hagemann, & Schubö, 2011; Schankin & Schubö, 2009) suggesting a more pronounced deployment of visual selective attention (Eimer, 2014; Luck & Hillyard, 1994; see also Tan & Wyble, 2015). This is also supported by empirical work applying eye tracking, which has demonstrated that the number of fixations decreases and scan paths become more direct in repeated contexts (Manginelli & Pollmann, 2009; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012). All these findings support the notion that attention is guided more efficiently to the target in repeated than in novel contexts.

Reward modulating contextual cueing

There is evidence for an interaction of reward and contextual cueing, i.e., reward accelerating context learning in contextual cueing paradigms. Tseng and Lleras (2013) examined whether reward had a direct impact on configuration learning in contextual cueing. They associated three outcome conditions (reward, loss, or no outcome) to a subset of repeated and novel contexts. Participants had to collect points that were awarded for correct responses and were told that a particular amount of points had to be reached to complete the experiments. Results showed faster development of the search time advantage for rewarded versus nonrewarded repeated displays, while the size of the contextual cueing effect was not affected. Moreover, consistent reward associations led to faster learning compared to variable associations, indicating that the valence of context-outcome associations had an impact on the consolidation of context information into memory.

Also relative reward magnitudes were reported to influence context learning. In a functional magnetic resonance imaging study, Pollmann et al. (2016) consistently associated individual contexts with either high or low monetary reward feedback. Participants worked through two separate contextual cueing sessions with reward being absent in the second session. Their results replicated Tseng and Lleras' finding of accelerated learning of repeated contexts when these were associated with reward. Interestingly, however, while repeated high-reward distractor configurations elicited a strong search advantage and were searched more efficiently also in the absence of reward, no such advantage was observed for low reward configurations. The authors suggested that the presence of two different reward magnitudes hindered learning in low reward trials and instead resulted in preferential allocation of limited resources to context learning in high reward contexts.

Although these studies have demonstrated the influence of reward on contextual cueing, it is still unclear to what extent attentional mechanisms are involved. Tseng and Lleras (2013) suggested that observers learned both, an association between a context and the position of the target, and an association between context and reward magnitude. They argued that reward feedback resulted in an increase in arousal which subsequently strengthened the consolidation process of context learning into memory. As contexts encoded at higher arousal were easier to retrieve, target detection was faster in future encounters of the same context.

Schlagbauer, Geyer, Müller, and Zehetleitner (2014), however, suggested that attentional weighting of individual target locations accounted for the observed acceleration of context learning. In their replication of the study of Tseng and Lleras (2013), they disentangled the effect of reward on context configuration learning and on target location learning. The authors presented repeated and newly generated distractor configurations associated with either a low or high reward magnitude. Importantly, they used separate target locations for repeated and novel contexts, and for high and low reward trials to assess whether reward influenced context learning and target location learning separately. With this design, high and low reward magnitude was associated with different target locations in novel contexts, and with both different target locations and context configurations in repeated contexts. As a result, they found reward effects also in novel contexts. These were actually larger than those observed in repeated context configurations. The authors concluded that observers, rather than learning an association of the repeated context and the reward magnitude, learned an association of the target location and the reward magnitude. They suggested that this association was learned in novel contexts, where the target location repeated, but also in repeated contexts, where both target location and context configuration repeated. The authors concluded that reward facilitated target location learning due to attentional weighting of those individual target locations that were associated with high reward. Accordingly, target locations which were followed by high reward feedback were preferably selected in the following trials (cf. Hickey et al., 2014), because increased attentional weights facilitated attention guidance toward these locations in future encounters—irrespective of repeated contextual regularities.

Also Sharifian et al. (2017) suggested that reward is associated with the target location in novel contexts. In contrast to Schlagbauer et al. (2014), they argued that in repeated contexts, when target location and context configuration repeated, the context configuration rather than the target location was associated with reward, resulting in the facilitation of context learning. The authors hypothesized that initially, both target location and repeated context configuration compete for an association in repeated contexts but that after a few repetitions, the context "wins" the competition against the target location. To test their hypothesis, the authors consistently associated novel and repeated contexts with either a low or a high reward. In contrast to Schlagbauer et al. (2014) they used the same target locations for novel and repeated contexts, but reward magnitude was consistently associated with a target location in only 50% of the trials. In the other trials, reward magnitude varied dependent on context type: In trials with variable reward magnitude, a target location was consistently tied to, e.g., high reward in novel contexts and low reward in repeated contexts. With this design, the authors found that reward facilitated context learning when the target location was consistently associated with reward. However, when the same target location was paired with high reward in novel and low reward in repeated contexts, they observed that context learning was reduced in the first blocks of the experiment. The authors concluded that this was resulting from the competition between context learning and target location learning. They interpreted that a high reward was associated with the target location in novel contexts and that this association interfered with the association of a repeated context and the same location. They suggested that this interference supported their hypothesis that the target location was associated with reward in novel contexts whereas in repeated contexts target location and context configuration initially competed for an association.

From the aforementioned it seems obvious that reward facilitates task performance in contextual cueing tasks either by leading to prioritized processing of associated repeated context configurations or by increasing the weight at associated target locations, or by both. In all aforementioned studies, however, reward feedback was associated with different context configurations that were generated by a combination of distractor orientations and distractor locations. In the present experiment, we used a different approach. Rather than associating reward magnitude with particular context configurations (i.e., a combination of distractor orientations and distractor locations), we used an additional response-irrelevant context feature, namely color, to signal reward magnitude. This reward-signaling color was available in both novel and repeated contexts with display onset. As outlined already, studies examining reward-driven attention capture often used particular stimulus features to signal subsequent reward magnitude (e.g., Anderson, Laurent, & Yantis, 2011; Hickey & van Zoest, 2013).

Rationale of the present study

In the present study, we used a salient yet response-irrelevant context feature (color) to signal the reward magnitude that could be received in each trial. Although the context configuration per se is not response-relevant in contextual cueing because participants have to respond to the orientation of the target letter T that varies randomly in each trial, the context configuration shares some features with the target, as all context elements (the letters L) are composed of horizontal and vertical lines, as is the target letter T. Since participants are instructed to report the orientation of the target, one might argue that line orientation as a feature is response-relevant. Color, as an additional context feature, is response irrelevant in this task. We associated reward to color rather than different context feature configurations, and we associated reward magnitude with the same color in both repeated and novel context configurations. We assumed that once the color-reward association had been established, participants could predict the expected reward magnitude directly with display onset without having to process the context configuration.

Former studies have coupled reward to particular context configurations or target locations; hence, participants had to process the context configurations to some extent to predict reward magnitude. Contrary to Schlagbauer et al. (2014), we used the same target locations for novel and repeated contexts and for all reward magnitudes. Target location therefore neither predicted the reward magnitude nor context novelty. This also differed from the study of Sharifian et al. (2017), as they shared target locations across novel and repeated contexts but associated locations with particular reward magnitudes in half of the trials. Since we associated reward to colored context items, we could use the same target locations in all experimental conditions.

Participants performed a standard contextual cueing task with reward feedback given after every trial. Half of the search display items were presented in one of three colors. Colors were associated with different reward magnitudes (low, medium, and high) in both repeated and novel contexts. As color was fully predictive of reward magnitude, we hypothesized that participants will learn to associate the color with the expected reward magnitude.

In contrast to previous work reward magnitude could be predicted from the search display directly in novel and repeated contexts, but it could not lead to differences in target location cueing. This approach allowed investigating to what extent reward contributes to contextual cueing, independent of location probability cueing and in addition to context configuration learning.

Reward learning might affect search performance in at least three ways in our task. First, reward learning might have a general boosting effect on search performance, resulting in a performance increase (faster response times) in high reward compared with medium and low reward trials that should be observed in both novel and repeated context configurations. Second, reward learning might lead to prioritized encoding of contextual configuration information of displays containing the reward-signaling color. This should manifest in faster response times for repeated compared with novel contexts that should be more pronounced in high reward compared with medium or low reward contexts. Finally, reward learning might boost contextual cueing by leading to more efficient attention guidance to the location of the target. More efficient attention guidance to the target should be observed when comparing the eye movement pattern in repeated and novel contexts associated with high, medium, and low reward: Initial saccades should land closer to the target location in repeated compared with novel contexts (e.g., Tseng & Li, 2004; Zhao et al., 2012) and this difference should be most pronounced in contexts associated with high reward.

Method

Participants

Twenty volunteers (14 female, six male) naïve to paradigm and objective took part in the experiment. Participants were aged 19–34 years ($M = 23.7$, $SD = 3.92$), had normal visual acuity, and showed no signs of visual achromatopsia (both tested with an Oculus Binoptometer 3; OCULUS Optikgeräte, Wetzlar, Germany). Participation was remunerated with payment or course credit. The experiment was conducted with the written understanding and consent of each participant in accordance with the ethical standards of the Declaration of Helsinki and was approved by the local Ethic Committee (Faculty of Psychology, Philipps-University Marburg).

Apparatus

Participants were seated in a comfortable chair in a dimly lit and sound attenuated room responding with buttons of a gamepad (Microsoft Sidewinder USB; Microsoft, Redmond, WA) in their hands. Participants placed their heads on a chinrest facing the center of the screen. Stimuli were presented on a LCD-TN screen (Samsung SyncMaster 2233RZ 22-in., 1680 × 1050 pixels; Samsung, Seoul, ROK) set to a refresh rate of 100 Hz. The screen was placed 100 cm in front of the participants. Eye movements were recorded with an EyeLink 1000 Plus desktop mounted eye tracker (SR Research Ltd., Ottawa, Canada) with a spatial resolution of 0.01° at a sampling rate of 1000 Hz. The device was calibrated using the EyeLink 13-point calibration procedure. A Windows 7 PC (iTMediaConsult, Züsch, Germany) running E-Prime Professional (Version 2.0.10.356; Psychology Software Tools, Sharpsburg, PA) controlled response collection and stimulus presentation.

Stimuli

Search context displays always consisted of 16 items, 15 L-shaped distractors, and 1 T-shaped target item, distributed on an imaginary 10 × 7 matrix (24.4° × 15.5°). Each L-shaped item was rotated either 0°, 90°, 180°, or 270°. T-shaped items were tilted left- or rightward. The size of both items was 1.10° × 1.10° with a minimum distance of 0.68° between two objects. Targets were presented at four locations, one placed in each quadrant of the search display at an eccentricity of 6.18° from screen center and with two-cell distance to the grid's outer edges. Distractors were placed at eight cells per hemifield (seven if the target was presented on the same side), which were chosen randomly within the matrix. Every context contained eight gray (RGB 102, 102, 102; 37.07 cd/m^2) and eight unitarily colored items presented on a dark gray background (RGB 60, 60, 60; 12.15 cd/m^2). The target was colored in 50% of all trials; in the other half it was presented in gray. Colored items could be green (RGB 0, 128, 21; 36.48 cd/m^2), orange (RGB 143, 95, 0; 36.90 cd/m^2), or purple (RGB 170, 0, 217; 36.81 cd/m^2). All colors were isoluminant to the gray items.

Procedure

Contextual cueing task

Trials started with a central fixation dot (Thaler, Schütz, Goodale, & Gegenfurtner, 2013) surrounded by a thin line. As soon as participants fixated an area of 1.4° around this dot for at least 350 ms, the thin line disappeared and the screen was replaced by the search display after 400 ms. Participants were instructed to search for the T-shaped target and correctly report its orientation by pressing a left or right button on the gamepad. The search display was presented until participants manually responded or replaced after 1,000 ms by a blank screen presented for 600 ms. As soon as a response was given, a feedback screen was showing point feedback at screen center for 600 ms. Correct responses were rewarded by "+1," "+5," or "+10" points, dependent on the color presented in the search context. Color and reward magnitude associations were constant for individuals during the experiment but were balanced across participants. Incorrect responses and responses slower than 1,600 ms were not rewarded but followed by "+0" feedback. Participants were not explicitly informed about the color and reward magnitude association but were told that they would be rewarded for correct responses in every trial. Points were translated into monetary reward (1 EUR for 1,000 points, max. 6.14 EUR) at the end of the experiment. Participants received the monetary reward in addition to the reimbursement for participation.

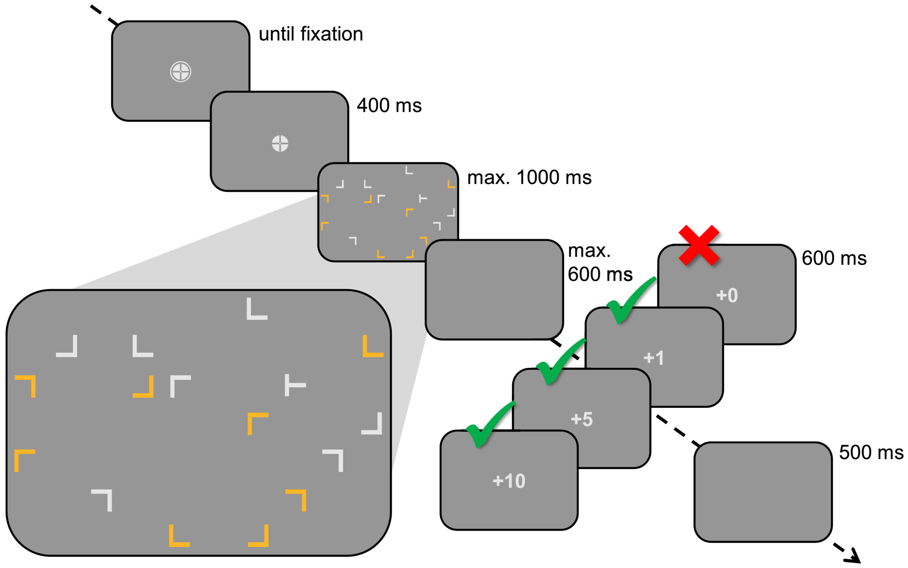

Figure 1. Trial procedure and exemplary search display. Participants were instructed to fixate the fixation dot to avoid eye movements before the search display was presented. The search display was shown until response or replaced after 1,000 ms by a blank screen. Participants searched for a T-shaped target among L-shaped distractors and reported the target's orientation by button press. After a response was given, a feedback screen presented point feedback. The amount of points depended on the color presented in the search display. Color-reward associations were balanced across participants. Correct answers were rewarded, only incorrect responses were followed by no reward ("+0").

Trial procedure and search display are depicted in Figure 1.

Experimental procedure

The experiment consisted of two sessions. Each session contained 12 blocks with 48 trials resulting in 1152 trials. For each participant, 24 repeated search contexts were generated individually. These contexts appeared repeatedly in each block of each session, randomly intermixed with 24 novel context configurations generated randomly for each trial. Both configurations were generated separately for contexts containing a colored or a gray target. Contexts were created for all combinations of the four target locations and three reward magnitudes. The same target locations were used in novel and repeated contexts and contexts associated with different reward magnitudes (cf. Figure 2). Assignment of reward magnitudes to colors was randomized and balanced across participants. Orientation of the T-shaped target was determined randomly in each trail, ensuring that repeated context configurations

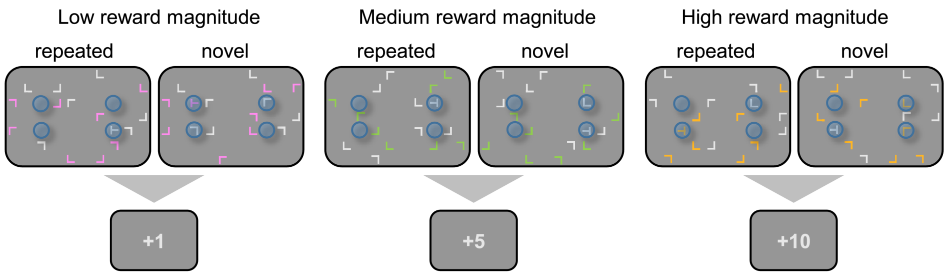

Figure 2. Target locations and exemplary search displays in novel and repeated contexts associated with different reward magnitudes. The same target locations (indicated by blue cycles) were used in repeated and novel contexts and in contexts associated with low, medium, and high reward. Color-reward associations were balanced across participants.

predicted the target location but not the target orientation, i.e., the correct manual response.

At the beginning of the first session, participants performed 48 practice trials consisting of only novel contexts without implementation of reward. When participants reached a response accuracy of at least 65%, they continued with the experimental task. Performance feedback consisting of mean response accuracy, response times, and total amount of points achieved was provided after each block, followed by an obligatory pause of at least 10 seconds between blocks. After session 1, participants returned within 3 days for session 2. No additional practice trials were performed in this session. A recognition task was performed at the end of session 2, followed by a follow-up survey investigating individual search strategies and recognized experimental regularities.

Recognition task

In the recognition task conducted at the end of the second session, 48 trials consisting of 24 repeated contexts were randomly intermingled with 24 novel contexts. Participants were informed that some contexts were repeated over time and asked to decide for each context whether it had been shown before. The recognition task had no time restriction and participants were asked to decide intuitively.

Data analysis

Response times and error rates

Reaction times (RT) and error rates were analyzed separately. Trials with incorrect responses and trials with exceedingly short or long RT (± 2 *SD* from mean RT, calculated separately for each participant and block) were removed from RT analysis ($M = 17.4$ %, $SD = 4.22$). Hierarchical linear mixed models (HLMs; e.g., Hox, 2002; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999) were applied to investigate the influence of reward magnitude on the reduction of response times in repeated relative to novel contexts. In contrast to usually implemented analyses of variance (ANOVA), HLMs allow to analyze context learning as developing differential reduction in RTs without reducing data by aggregating blocks into epochs. Using HLMs allows ability to include data based on the experimental factors in every single trial and to control for the dependent data structure. As participants took part on two days, sessions were modeled on the second, participants on the first level of data analysis. As we expected participants to show inter-individually varying levels of RTs, we included random intercepts and slopes for each participant and session. Fixed effects, which might be compared with within-subject factors of ANOVA analyses, included the effects of blocks (0–23, block coded as block–1 for better interpretation), context type (novel vs. repeated contexts), medium reward magnitude (low vs. medium), high reward magnitude (low vs. high), and experimental session (1 vs. 2). Blocks were included as time variable, as the HLM was analyzing the decline of response times in the course of the experiment. The two-way interaction of blocks and context type described the emerging differences in RTs between novel and repeated contexts. The three-way interactions: blocks $\times$ context type $\times$ medium reward, blocks $\times$ context type $\times$ high reward, and blocks $\times$ context type $\times$ session, were included in the HLM. These interactions represented differences in context learning between the different reward magnitudes during the experiment, and differences in context learning between the first and second session. Model parameters were estimated by applying maximum likelihood method. Data was evaluated using IBM SPSS Statistics 24 (IBM, Armonk, NY).

Additionally, the influence of received reward magnitudes in trial n–1 on task performance in trial n was analyzed using similar HLMs. Within these models, reward magnitude in trial n–1 was applied for predicting performance measures in trial n.

The analysis was averaged across contexts in which the target was colored or gray. Since both types were presented equally likely, participants could neither benefit from searching only the gray nor only the colored items. One may, however, assume that participants prioritized colored compared with gray targets, since the color was associated to reward magnitude. This would lead to reward influencing task performance stronger in contexts with colored compared with gray targets. To examine whether reward had a differential influence on contextual cueing in displays with colored and displays with gray targets, we divided the data into two sets (displays with colored and displays with gray targets) and computed the HLM described previously separately for both context types. In addition, we directly compared task performance in contexts with gray and colored targets. We ran a repeated-measure ANOVA with the three factors target color (gray vs. colored), context novelty (novel vs. repeated), and reward (low. vs. medium vs. high reward).

Recognition task

Accuracy in the recognition task was examined by a 2 $\times$ 3 repeated-measure ANOVA with the within-subject factors context type (novel vs. repeated contexts) and reward magnitude (low vs. medium vs. high reward).

Eye movements

Saccades, fixations, and blinks were detected applying the SR Research parser. Saccades were defined by the

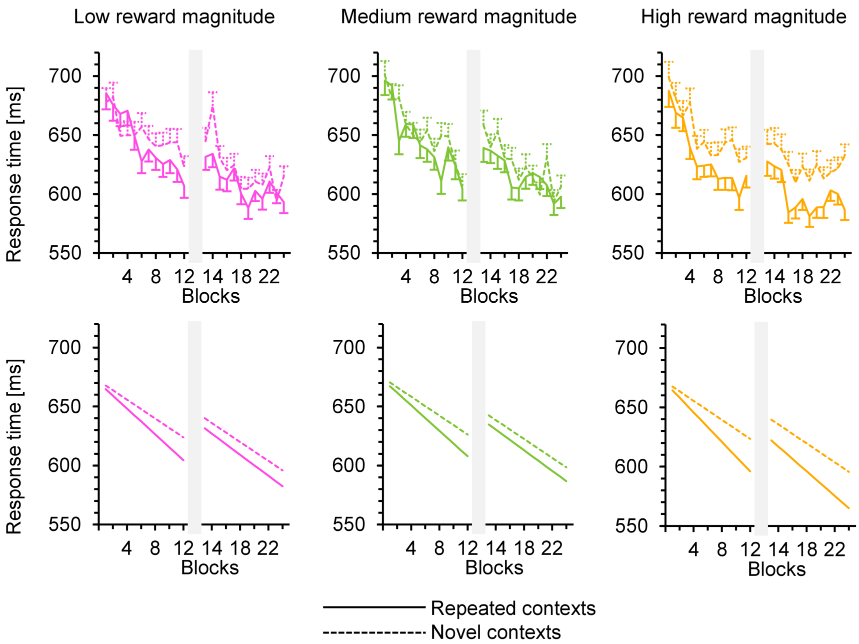

Figure 3. Observed response times (upper row) for novel (dotted lines) and repeated (solid lines) contexts associated with low (left panel), medium (middle panel), and high (right panel) reward. The predicted values based on the calculated HLM are depicted in the row below the observed values (lower row). Low, medium, and high reward magnitudes are also indicated by different colors. The gray bar depicts the time gap (1–2 days) between the two experimental sessions. Error bars denote the standard error of the mean.

combination of minimum velocity of 30°/s and acceleration of 8,000°/s^2. For further analyses, eye position data was transformed into degrees of visual angle. Trials with incorrect responses, first saccade latencies smaller than 100 ms, and trials in which participants blinked were removed, resulting in 22.0% ($SD = 6.91$) of trials being discarded from following analyses. The remaining data was evaluated applying the same HLMs as used for response times. An additional fixation accuracy measure was implemented, depicting whether participants stayed within 2° around the target location before a manual response was given. Due to technical issues, eye movements could only be recorded for 19 out of 20 participants. The eye movement results were based on the data of these 19 participants.

Results

Response times

At the beginning of the experiment, response times in novel ($M_{\text{Block1}} = 694.64$ ms, $SD = 67.26$) and repeated contexts ($M_{\text{Block1}} = 693.41$ ms, $SD = 70.91$) did not differ significantly, as the main effect of context type did not reach statistical significance, $F(1, 13513) = 0.58$, $p = 0.448$, cf. Figure 3, upper row. As the experiment proceeded, participants became faster responding to targets in repeated compared to novel contexts, which was indicated by a significant interaction of blocks and context type, $F(1, 6878) = 5.18$, $p = 0.023$. This effect developed during the experimental course ($\Delta M_{\text{Block1}} = 1.23$ ms, $SD = 48.53$; $\Delta M_{\text{Block24}} = 24.34$ ms, $SD = 25.71$) and was reflected in the predicted values based on the HLM's regression coefficients, cf. Figure 3, lower row. The RT difference between novel and repeated contexts predicted by the HLM increased by an average of 1.47 ms with each subsequent block, $b = -1.47$, $SE_b = 0.64$, $t(6878) = -2.28$, $p = 0.023$, starting with the second block in session 1. Importantly, participants responded faster to targets presented in repeated high reward ($M = 614.41$ ms, $SD = 52.20$) compared with repeated low reward contexts ($M = 627.46$ ms, $SD = 56.63$), an effect that developed during the experimental course and became visible as a significant three-way interaction of high reward magnitude, blocks and context type, $F(1, 18950) = 8.66$, $p = 0.003$. This was visible in contexts with a gray target, $F(1, 9273) = 5.29$, $p = 0.021$, and with a colored target, $F(1, 9589) = 3.95$, $p = 0.047$. RT decreases of repeated contexts associated with medium and low reward magnitude did not differ significantly, as the relating interaction (blocks × context type × medium reward) did not reach statistical significance, $F(1, 18951) = 0.09$, $p = 0.762$. The general level of response times did not differ between high and low as well as medium and low reward contexts, as neither the main effect of medium (vs. low) reward magnitude, $F(1, 18951) = 1.01$, $p = 0.315$, nor of high (vs. low) reward magnitude, $F(1, 18951) = 0.02$, $p = 0.896$, reached statistical significance ($M_{\text{Low}} = 630.59$ ms, $SD = 52.19$; $M_{\text{Medium}} = 634.03$ ms, $SD = 51.53$; $M_{\text{High}} = 625.57$ ms, $SD = 63.61$). In session 2, differences between repeated and novel contexts' RTs were maintained but less pronounced: The HLM predicted that the RT difference between novel and repeated contexts only increased by an average of 0.45 ms with each subsequent block in session 2, which was indicated by an interaction of block, context type, and session, $F(1, 5124) = 4.66$, $p = 0.031$. The positive predictor value of this interaction indicates a shallower predicted RT decrease in repeated contexts in session 2 compared to session 1, $b = 1.02$, $SE_b = 0.47$, $t(5124) = 2.16$, $p = 0.031$.

Response times gradually decreased during the experiment with increasing block number ($M_{\text{Block1}} = 693.29$ ms, $SD = 64.10$; $M_{\text{Block24}} = 604.70$ ms, $SD = 51.33$) indicated by a main effect of blocks, $F(1, 25.6) = 41.31$, $p < 0.001$. The HLM predicted a response time decrease by an average of 4.0 ms with each subsequent block, $b = -4.00$, $SE_b = 0.62$, $t(25.6) = -6.43$, $p < 0.001$. Response times were slower at the beginning of the second ($M_{\text{Block13}} = 639.60$ ms, $SD = 75.84$) compared with the end of the first ($M_{\text{Block12}} = 615.06$ ms, $SD = 51.50$) session of the experiment, $F(1, 25.7) = 6.02$, $p = 0.021$. This response time increase might have been due to the missing practice trials in session 2, as participants might have needed some trials to get used to the task again. Since this increase was similar in repeated and novel contexts and in different reward magnitudes, the missing practice might have led to a general, nonspecific performance loss, which became visible in longer response times in the first block of session 2. In line with this conclusion, studies using practice trials also in session 2 (e.g., Chun & Jiang, 2003) found no general increase in the first block of the second session (see also Jiang et al., 2005).

The three-way interaction of block, context type, and reward magnitude was further investigated by HLMs calculated separately for each reward magnitude. The models specified were the same as the main model, but excluded the main and interaction effects of reward magnitude. Although a significant interaction of blocks and context type was observed for low, $F(1, 1426) = 5.44$, $p = 0.020$, and high reward contexts, $F(1, 6941) = 6.23$, $p = 0.013$, this interaction missed statistical significance for medium reward contexts, $F(1, 1149) = 0.86$, $p = 0.355$.

If reward learning had a general boosting effect on search performance, a performance increase in high reward contexts should be observable in both novel and repeated context configurations. To examine this notion, we additionally examined search performance separately for novel and repeated contexts associated with different reward magnitudes. The HLM was specified as the main model, with the main and interaction effects of context type excluded, as we now analyzed performance separately for each context type. In repeated contexts, high (vs. low) reward led to shorter response times ($M_{\text{High}} = 614.4$ ms, $SD = 52.20$; $M_{\text{Low}} = 627.5$ ms, $SD = 56.63$), $F(1, 9674) = 22.01$, $p < 0.001$, while no difference was observed for medium (vs. low) reward ($M_{\text{Medium}} = 630.3$ ms, $SD = 56.67$), $F(1, 9676) = 0.85$, $p = 0.358$. In novel contexts, neither high (vs. low) reward, $F(1, 9205) = 1.30$, $p = 0.254$, nor medium (vs. low) reward magnitude influenced response times, $F(1, 9204) = 1.52$, $p = 0.218$, ($M_{\text{High}} = 638.3$ ms, $SD = 59.25$; $M_{\text{Medium}} = 638.7$ ms, $SD = 50.03$; $M_{\text{Low}} = 634.5$ ms, $SD = 51.01$).

Reward magnitudes received in trial n–1 did not influence response times in trial n. When the reward magnitude received in trial n–1 was applied for predicting response times in trial n, neither did the interaction of block, context type, and received medium reward magnitude reach statistical significance, $F(1, 18942) = 0.42$, $p = 0.517$; nor did the interaction of block, context type, and received high reward magnitude, $F(1, 18935) = 1.34$, $p = 0.247$.

To compare whether response times differed across contexts with gray and colored targets, we additionally ran a repeated-measure ANOVA with the three factors target color (gray vs. colored), context novelty (novel vs. repeated), and reward magnitude (low vs. medium vs. high reward). Response time results showed no significant differences between contexts with gray ($M = 634.33$ ms, $SD = 60.75$) and colored targets ($M = 628.71$ ms, $SD = 54.22$), as the main effect and any interactions including the target color failed to reach significance (all $ps > 0.173$).

In sum, the results show that participants responded faster to targets in repeated compared with novel contexts, an effect which developed during the experiment. The differences between repeated and novel contexts' RTs appeared fastest and were most pronounced in the high reward condition.

Error rates

Participants' search accuracy was comparatively high, reflected in low error rates ($M = 14.0\%$, $SD = 34.70$). Error rates significantly decreased during the experiment, $F(1, 122247) = 53.44$, $p < 0.001$. The predicted error rates by the HLM decreased by an

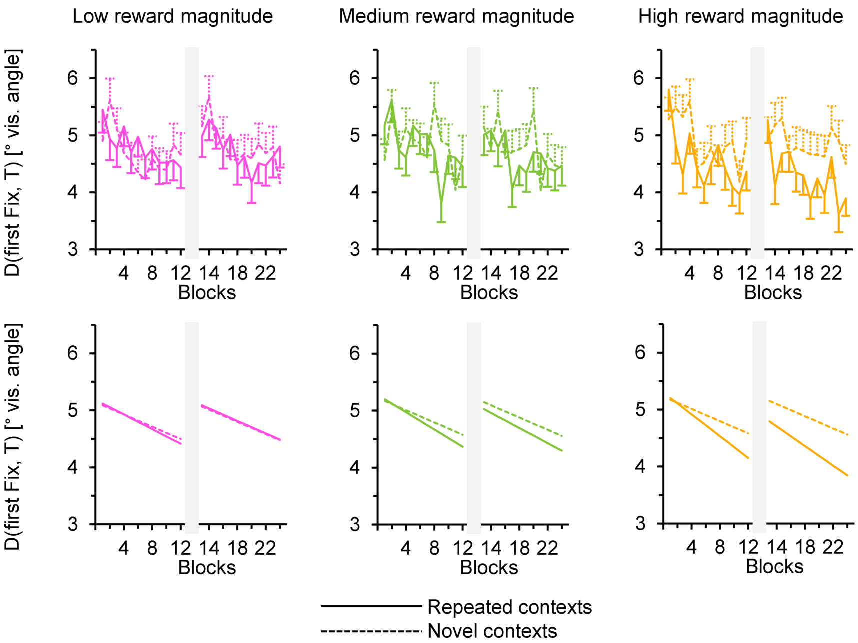

Figure 4. Distance of the first fixation to the target location (upper row). The predicted values based on the calculated HLM are depicted in the row below the observed values (lower row). Associated reward magnitudes are indicated by different colors and displayed in separate diagrams in columns one to three. Solid lines indicate performance in repeated, dotted lines in novel context configurations. The gray bar depicts the time gap between the two experimental sessions. Error bars denote the standard error of the mean.

average of 0.9% with each subsequent block, $b = -0.94$, $SE_b = 0.13$, $t(22981) = -7.31$, $p < 0.001$. Participants made more errors in novel contexts ($M = 15.59\%$, $SD = 5.65$) compared with repeated contexts ($M = 12.41\%$, $SD = 5.06$), $F(1, 23962) = 5.36$, $p = 0.021$. The interactions of blocks and context type, $F(1, 25148) = 2.17$, $p = 0.642$, as well as blocks, context type and session, $F(1, 25721) = 0.23$, $p = 0.631$, missed statistical significance. All other main and interaction effects showed no significant influences (all $ps \geq 0.197$). These results show that participants made fewer errors during the experimental course. They also made fewer errors in repeated compared with novel contexts, while no differences between contexts associated with different reward magnitudes could be observed.

Eye movements

Analogous to the analysis of response times, the predicted distance between first fixation and target location gradually decreased during the experimental course with increasing block number, $F(1, 222) = 19.57$, $p < 0.001$, cf. Figure 4, upper row. The predicted distance of 5.09° in block 1, $b = 5.09$, $SE_b = 0.16$, $t(31.51) = 31.02$, $p < 0.001$, decreased on average by 0.05° with each subsequent block, $b = -0.05$, $SE_b = 0.01$, $t(222) = -4.42$, $p < 0.001$. Comparable with response time results, this distance was larger at the beginning of the second compared with the end of the first session, yielded by a significant main effect of session, $F(1, 272) = 17.86$, $p < 0.001$. In repeated contexts associated with high reward magnitude, estimated distances decreased on average by 0.03° faster per block than distances in low reward repeated contexts, $b = -0.03$, $SE_b = 0.01$, $t(16890) = -3.43$, $p = 0.001$. This was yielded by a significant interaction of blocks, context type, and high reward magnitude, $F(1, 16890) = 11.75$, $p = 0.001$. Analogous to response times, this effect was visible in contexts with a gray, $F(1, 8395) = 5.91$, $p = 0.015$, and a colored target, $F(1, 9594) = 5.65$, $p = 0.018$. However, faster distance decrease could only be observed in the high reward condition, as the interaction of block and context type did not reach statistical significance, $F(1, 11001) = 0.23$, $p = 0.633$. No other main effects or interactions were significant (all $ps \geq 0.202$). Congruent to the evaluation of response times, reward magnitudes in trial n–1 did not influence eye movements in trial n. The observed interaction of blocks, context type, and high reward magnitude missed statistical significance when the reward magnitude in trial n−1 predicted the distance of the first fixation to the target location in trial n, $F(1, 16995) = 1.86$, $p = 0.173$. Distances of the first fixation to the target location predicted by the HLM are shown in Figure 4, lower row.

Analogous to response times, we examined whether the distance of the first fixation differed across contexts with gray and colored targets. We ran the same repeated-measure ANOVA with the three factors target color (gray vs. colored), context novelty (novel vs. repeated), and reward (low. vs. medium vs. high reward). Again, we observed no differences between contexts with gray ($M = 4.77°$, $SD = 0.93$) and colored targets ($M = 4.74°$, $SD = 0.87$), as the main effect and any interactions including the target color failed to reach significance (all $ps > 0.323$).

To examine whether reward influenced attention guidance also beyond the first fixation, we additionally analyzed the fixation count. This measure is known to be related to efficiency in visual search, as there is evidence that faster response times in repeated compared with novel contexts are accompanied by fewer total fixations (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Zhao et al., 2012). Accordingly, participants not only respond faster in repeated contexts but also needed fewer fixations to find the target. Fewer total fixations in high reward repeated contexts therefore also suggest that attention guidance was facilitated by reward. Results were similar to those observed with first fixation results: Only in high reward trials, the fixation count was significantly lower in repeated ($M = 2.12$; $SD = 0.32$) compared with novel contexts ($M = 2.24$; $SD = 0.35$), $F(1, 16983) = 9.58$, $p = 0.002$. This effect also developed during the experiment and could only be observed in the high reward condition, as the interaction of block and context type did not reach statistical significance, $F(1, 2804) = 2.08$, $p = 0.150$. Participants made two to three fixations on average in a trial ($M = 2.20$; $SD = 0.33$).

To investigate whether reward had an effect on postselective processes in our task, we also analyzed mean fixation durations. Fixation durations are related to the speed of object processing and to the selection of the next fixation, as studies suggested that during the fixation of an object the next fixation is planed simultaneously to object processing (e.g., Herwig & Schneider, 2014; Ludwig, Davies, & Eckstein, 2014). Results showed neither an effect of reward nor context novelty on mean fixation durations (all $ps > 0.121$).

Participants started to move their eyes 196 ms ($SD = 68.6$) after stimulus onset on average. They fixated the target location before giving a correct manual response in 95.5% of trials. When participants fixated the target before responding, fewer response errors were made, $r = -0.29$, $p < 0.001$ (correlation reported as two-tailed Pearson coefficient).

In sum, these results show that only in high reward contexts the distance between first fixation and target location was shorter in repeated compared with novel contexts and that this difference evolved during the course of the experiment.

Recognition task

Participants did not reliably differentiate between novel (47.3% correctly identified contexts, $SD = 9.68$) and repeated contexts ($M = 55.6$ %, $SD = 13.47$), as the statistical comparison failed to reach significance, $F(1, 19) = 4.20$, $p = 0.055$, $\eta_p^2 = 0.181$. Neither reward magnitude nor the interaction of context type and reward magnitude showed an effect on recognition accuracy, $F(2, 38) = 0.92$, $p = 0.406$, $\eta_p^2 = 0.046$; $F(2, 38) = 0.45$, $p = 0.956$, $\eta_p^2 = 0.002$.

When asked for recognized experimental regularities in the follow-up survey, three out of 20 participants stated that they had recognized the (correct) association between color and reward magnitude.

Discussion

This study investigated the influence of expected reward outcomes on contextual cueing by using context configurations that contained colored context items that were associated with different reward magnitudes. We expected reward magnitude to modulate contextual cueing, with high reward leading to larger (cf. Pollmann et al., 2016), and faster emerging (cf. Tseng & Lleras, 2013) differences between repeated and novel context configurations. The implemented HLMs used to analyze the results provided several advantages. The model was specified with to comply with the hierarchical data structure and according to specific hypotheses about the impact of reward on contextual cueing. Reward learning was decoupled from both, context configuration and target location, as reward magnitude was associated with a salient, response-irrelevant context feature (color). Thus, the same target locations could be used in novel and repeated contexts, and both context types could be combined with all three reward magnitudes. Participants could predict the reward magnitude from the color with display onset in both novel and repeated contexts.

Our findings showed a faster decline of response times in repeated compared with novel contexts, an effect that was more pronounced and emerged earlier in contexts associated with high reward. Contextual cueing became also visible in the analysis of eye movement patterns: The distance of the first fixation to the target location decreased in repeated compared with novel contexts, an effect that was observed only in contexts associated with high reward. These results suggest that reward learning not only resulted in contextual cueing in repeated contexts associated with high reward, but was also accompanied by faster and more efficient detection of the target in repeated context configurations.

Taken together, these findings demonstrate that high reward facilitates learning of context configurations containing the reward-signaling color. Moreover, reward learning also leads to more efficient attention guidance toward the target location in the course of the experiment.

Reward facilitates context configuration learning

In line with Tseng and Lleras (2013), we observed no main effect of reward but an accelerated response time decrease in repeated high reward contexts (but see Schlagbauer et al., 2014). Associating high reward with context color thus led to a more pronounced contextual cueing effect and not to a general boost of search performance. A possible theoretical explanation of these results was suggested by Tseng and Lleras (2013). In their study, the authors explained the accelerated contextual cueing effect in rewarded contexts by referring to an increase in arousal. They assumed that receiving a reward enhanced the observer's arousal, which in turn altered the memory consolidation process of the rewarded context. A state of high arousal thus strengthened the consolidation of the rewarded context into memory, resulting in faster retrieval on future encounters of the same context. Faster retrieval in turn resulted in faster target detection in rewarded contexts.

Evidence for this arousal hypothesis comes from a result of their second experiment (Tseng & Lleras, 2013: experiment 2) in which participants experienced an unexpected point penalty when they had expected to obtain a reward. Results showed that experiencing an unexpected point penalty when expecting a reward immediately accelerated learning of the associated context, an effect that was observed in the subsequent block. The authors assumed that the unexpected outcome gave rise to "surprise," which triggered more arousal than any expected outcome might have and eventually resulted in an immediate enhanced consolidation of the context into memory and in large contextual cueing effects.

The present study extended the results of Tseng and Lleras (2013) by showing that high reward and arousal actually facilitated context configuration learning and did not result in an unspecific reward benefit. Contrary to Tseng and Lleras (2013), reward was associated with a salient color rather than with a particular context configuration (i.e., a combination of distractor orientations and distractor locations), and the same color was used in both repeated and novel contexts. This allowed disentangling context configuration learning from a more general arousal effect. As the decrease in response time shows, participants quickly learned the association between color and subsequent reward magnitude. Thus after several trials, they were able to predict the expected reward outcome already with onset of the search display. If we assume that expecting a high reward outcome triggers more arousal than expecting a low reward outcome, an impact of arousal on context configuration learning should become manifest as response time benefits only in those contexts that were repeated in the course of the experiment. A general arousal effect, on the other hand, should have boosted response times in both context types.

Our results showed a response time benefit for repeated contexts associated with high reward, that is, only when context configurations were repeated in the course of the experiment. Following the notion of Tseng and Lleras (2013), we conclude that memory consolidation was strengthened with each repetition of a context configuration, and that this effect was enhanced when contexts were associated with high reward. High arousal levels during encoding also allowed faster retrieval of repeated contexts, resulting in faster target detection than in contexts associated with low reward and in novel contexts. As novel contexts were generated randomly in each trial, performance could not benefit from higher arousal in high reward trials. Thus, high reward was efficient in repeated contexts, because it facilitated learning of context configuration regularities. Target detection benefited indirectly, as attention could be guided faster to the target location in repeated contexts.

Interestingly, a pronounced contextual cueing effect was mainly observed in contexts associated with high reward while the effect was much smaller or virtually absent in contexts associated with low and medium reward. Evidence showing that contextual cueing is not very pronounced in contexts associated with a low (relative to high) reward magnitude has been reported already elsewhere (Pollmann et al., 2016; Sharifian et al., 2017). These findings might seem puzzling at first, since a large number of contextual cueing studies have reported contextual cueing without assigning any reward. A possible explanation might lie in the limited processing resources available for context learning (Pollmann et al., 2016; Schlagbauer, Müller, Zehetleitner, & Geyer, 2012; Smyth & Shanks, 2008). Some studies used quite larger numbers of repeated contexts that were divided across different experimental conditions. As a result, each context received only little capacity for encoding, storage and retrieval. If these contexts are associated with different reward magnitudes, participants might allocate most of their resources to high reward contexts leaving little or no capacity for contexts associated with medium or low reward (Pollmann et al., 2016). In the present study, 24 repeated context configurations were divided into three reward magnitudes, making it rather likely that participants had to allocate their resources. Thus, processing limits might have contributed to the results.

At first glance, our interpretation that little or no capacity was left for low and medium reward context learning seems contradictory to the results of Jiang et al. (2005), who had hypothesized that observers were able to learn far more than 12 repeated contexts, the amount used in most contextual cueing studies. To examine this notion, they conducted five training sessions of different contextual cueing tasks on five consecutive days. In each session, participants learned 12 unique repeated contexts that differed from the other sessions. In a sixth session 1 week after the last training session, the authors presented all 60 learned contexts, now randomly intermixed with 60 novel contexts. Jiang et al. (2005) observed contextual cueing for all contexts of the five training sessions and concluded that observers have a high capacity for context learning in contextual cueing. The present study used only 24 repeated contexts, less than half as many as Jiang et al. (2005). Contrary to the study of Jiang et al. (2005), however, participants had to learn twice as many contexts in one experimental session. Schlagbauer et al. (2012) suggested that only about four repeated contexts out of 12 can actually be learned in an experimental session (Schlagbauer et al., 2012). When we assume that participants learn only a subset of repeated contexts due to a limitation of resources for context learning, it might be rather likely that reward increases the probability that limited resources are allocated to high reward and not to medium or low reward contexts (see also Pollmann et al., 2016). This might be especially the case in our study, since reward magnitude could be predicted directly from the color.

Reward learning and attention guidance

In addition to response times, eye movement measures were used to analyze search performance. Prior studies have reported that context learning manifested in more precise first fixations with respect to the target location (Manginelli & Pollmann, 2009; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012). Although participants were not explicitly instructed to move their eyes in our task, we hypothesized more efficient attention guidance might manifest when comparing eye movement patterns in repeated and novel contexts associated with different reward magnitude.

Indeed, eye movements showed similar contextual cueing effects as observed for response times. Eye movements to the target location preceded correct responses, as indicated by the reported correlation between target fixations and response accuracy. The first fixation landed closer to the target location when the target was presented in a repeated context associated with high reward compared with targets that were presented in novel contexts or targets in contexts associated with low reward. Participants made fewer fixations in repeated contexts associated with high reward compared to novel contexts or contexts associated with low reward. Both, more effective first fixations and the reduced fixation count in repeated contexts indicate that participants could use retrieved contextual information for more efficient target localization. Mean fixation durations, however, were neither influenced by reward nor by context novelty, indicating that neither reward nor context novelty affected post-selective processes (e.g., Herwig & Schneider, 2014; Ludwig et al., 2014). These findings support the assumption that context learning manifests in more efficient attention guidance, and that this effect is supported by high reward.

Interestingly, more efficient attention guidance was again only visible with high reward and virtually absent in medium or low reward repeated contexts. As described already, this difference might have resulted from differential allocation of processing resources: Participants might have allocated most of their resources to high reward contexts, leaving little or no capacity for contexts associated with medium or low reward. This might also hold for the allocation of attention, especially as for each participant, reward magnitude was consistently associated with the same color feature, that is, color reliably predicted the reward outcome. As color was salient, preferential allocation of processing resources to high reward contexts seems even more likely.

We assume that the salient reward-signaling colors and the limits in context configuration learning might have contributed to the missing first fixation effect in medium and low reward contexts. We suggest that participants allocated most of their resources to contexts signaling high reward (cf. Pollmann et al., 2016), but also perceived these contexts as more salient than low or medium reward contexts, as there is evidence that reward can add to the salience of stimuli (e.g., Hickey et al., 2010). The preferential allocation of resources and the increased salience of high reward contexts might have led to a prioritization of context learning in high compared with medium and low reward contexts. If participants have learned high reward repeated contexts faster than medium or low reward contexts, also recognition of such contexts might have been faster. With faster recognition, information about the target location might have already been available in repeated contexts at the time the first saccade was planned, resulting in first fixations that landed closer to the target. This might explain why we observed first fixation effects in high, but not in low and medium reward repeated contexts.

In sum, expecting a high reward not only facilitated context configuration learning, but also led to more efficient attention guidance to the target when context configuration repeated. As in the response time results, we found no evidence for reward effects in novel contexts when they were associated with high reward. In contrast, Schlagbauer et al. (2014) reported faster response times also for targets presented in novel contexts when these were associated with different reward magnitudes. Importantly, however, in their experiment individual target locations were directly associated with high and low reward, and separate target locations were used for targets in novel and repeated contexts. Results showed that participants learned these particular location-reward associations for both context types, as high reward magnitude facilitated target detection also in novel contexts. The authors concluded that participants had learned to assign different attentional weights to target locations irrespective of the context configuration repetition (Schlagbauer et al., 2014).

The present data showed a response time benefit with high reward only for context configurations that were repeated in the course of the experiment. Search performance in novel contexts was not affected by reward because the same target locations were used in both context types, and they were associated with all three reward conditions. Thus, neither reward magnitude nor context novelty was predictive for particular target locations (and vice versa). In fact, our results showed that reward affected behavioral search performance (i.e., target responses, Figure 3) and eye movements (first fixations, Figure 4) in a rather similar way, as both underwent a similar development in the course of the experiment. It seems as if participants had to learn that particular context configurations come with particular target locations for reward to become effective. Such learning was possible only when context configurations repeated.

As outlined already, we assume that memory consolidation was strengthened with each repetition of a context configuration, and that this effect was enhanced when contexts were associated with high reward. Similarly, one might assume that target locations linked with a particular context configuration receive strengthening with every context repetition, which is enhanced in high reward contexts. Such strengthening might be part of context configuration learning, as with context configuration learning, the link between a particular context configuration and the respective target location is strengthened as well. Alternatively, target locations might be strengthened directly, for instance, because they receive a form of special weighting because the target location information is needed for search performance responses (see Schlagbauer et al., 2012, for a similar notion). Although our results are not decisive with respect to this point, weighting of target locations is a well-known factor in attention guidance and weighting of locations, which are associated with a high reward (and inhibition of locations associated with low reward) has been reported before (cf. Heuer, Wolf, Schütz, & Schubö, 2017; Hickey et al., 2014; Wolf, Heuer, Schubö, & Schütz, 2017).

In sum, our results provide evidence that once the link between a particular context configuration and the respective target location has been learned, attention guidance is facilitated toward this location with each context repetition. Facilitated attention guidance manifested in more precise eye movements, as the first fixations landed closer to the target with each repetition of a context associated with high reward.

Prediction and attention guidance

In our design, a color feature was consistently associated with the same reward magnitude; hence, each color feature reliably predicted the reward outcome. The differences observed in context learning can therefore not be attributed to different predictability of the reward signaling stimuli (cf. Tseng & Lleras, 2013).

Gottlieb (2012) suggested three different mechanisms according to which organisms allocate their attention. In natural behavior, these mechanisms serve different functions in guiding behavior. First, an organism allocates attention to the stimulus that has the highest probability of delivering the most valuable information for an upcoming action. This mechanism is labeled "attention for action." In learning environments, organisms attend to stimuli that are likely to reduce uncertainty. This mechanism ("attention for learning") ensures attending to novel and unknown stimuli, which have an uncertain predictability but can result in a large information gain. The third mechanism, "attention for liking," takes the expected value of signaled rewards into account. According to this mechanism, stimuli associated with high reward magnitude receive higher weights in attention guidance and are thus prioritized.

"Attention for liking" fits well with the finding of more efficient attention guidance in high reward repeated contexts. Participants neither were instructed to perform eye movements in our task, nor were eye movements associated with any response outcome such as reward. In natural behavior, the role of vision is to provide the relevant information needed for decision-making, and gaze is used to acquire this kind of information (Hayhoe, 2017, 2018; Hayhoe & Ballard, 2014; Tatler, Hayhoe, Land, & Ballard, 2011). Following these considerations, the finding that eye movements were more efficiently guided to the target location in repeated contexts seems to reflect a behavior that was more and more refined as the observer has learned to attend to the location, which contains the most relevant information (the target). The fact that this effect was more pronounced in contexts associated with high reward emphasizes the role of motivational value in learning.

Conclusion

The present findings indicate that context configuration learning is magnified and accelerated by the anticipation of high reward magnitude. When a salient context feature signaled high reward, an increased contextual cueing effect manifested in shorter response times in repeated relative to novel contexts. Reward expectation did not lead to a general boost of search performance, as performance in novel contexts was unaffected. At the same time, eye movements landed closer to targets in repeated contexts, which were associated with high reward. Taken together, the results show that high reward facilitates context learning and guides attention more efficiently to the target.

Keywords: reward, attention guidance, contextual cueing

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References

Anderson, B. A. (2013). A value-driven mechanism of attentional selection. *Journal of Vision*, *13*(3):7, 1–16, https://doi.org/10.1167/13.3.7. [PubMed] [Article]

Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39. https://doi.org/10.1111/nyas.12957

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

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

Bucker, B., Belopolsky, A. V., & Theeuwes, J. (2014). Distractors that signal reward attract the eyes. *Visual Cognition*, *23*(1-2), 1–24. https://doi.org/10.1080/13506285.2014.980483

Chelazzi, L., Perlato, A., Santandrea, E., & Della Libera, C. (2013). Rewards teach visual selective attention. *Vision Research*, *85*, 58–72. https://doi.org/10.1016/j.visres.2012.12.005

Chun, M. M. (2000). Contextual cueing of visual attention. *Trends in Cognitive Sciences*, *4*(5), 170–178. https://doi.org/10.1016/S1364-6613(00)01476-5

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: implicit learning and memory of visual context guides spatial attention. *Cognitive psychology*, *36*(1), 28–71. https://doi.org/10.1006/cogp.1998.0681

Chun, M. M., & Jiang, Y. (1999). Top-down attentional guidance based on implicit learning of visual covariation. *Psychological Science*, *10*(4), 360–365. https://doi.org/10.1111/1467-9280.00168

Chun, M. M., & Jiang, Y. (2003). Implicit, long-term spatial contextual memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(2), 224–234. https://doi.org/10.1037/0278-7393.29.2.224

Chun, M. M., & Turk-Browne, N. B. (2007). Interactions between attention and memory. *Current opinion in neurobiology*, *17*(2), 177–184. https://doi.org/10.1016/j.conb.2007.03.005

Della Libera, C., & Chelazzi, L. (2006). Visual selective attention and the effects of monetary rewards.

Psychological Science, *17*(3), 222–227. https://doi.org/10.1111/j.1467-9280.2006.01689.x

Della Libera, C., & Chelazzi, L. (2009). Learning to attend and to ignore is a matter of gains and losses. *Psychological Science*, *20*(6), 778–784. https://doi.org/10.1111/j.1467-9280.2009.02360.x

Driver, J. (2001). A selective review of selective attention research from the past century. *British Journal of Psychology*, *92*(1), 53–78. https://doi.org/10.1348/000712601162103

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

Failing, M., Nissens, T., Pearson, D., Le Pelley, M., & Theeuwes, J. (2015). Oculomotor capture by stimuli that signal the availability of reward. *Journal of neurophysiology*, *114*(4), 2316–2327. https://doi.org/10.1152/jn.00441.2015

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. (2014). Stimulus homogeneity enhances implicit learning: Evidence from contextual cueing. *Vision Research*, *97*, 108–116. https://doi.org/10.1016/j.visres.2014.02.008

Gottlieb, J. (2012). Attention, learning, and the value of information. *Neuron*, *76*(2), 281–295. https://doi.org/10.1016/j.neuron.2012.09.034

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Harris, A. M., & Remington, R. W. (2017). Contextual cueing improves attentional guidance, even when guidance is supposedly optimal. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(5), 926–940. https://doi.org/10.1037/xhp0000394

Hayhoe, M., & Ballard, D. (2014). Modeling task control of eye movements. *Current Biology*, *24*(13), R622–R628. https://doi.org/10.1016/j.cub.2014.05.020

Hayhoe, M. M. (2017). Vision and action. *Annual Review of Vision Science*, *3*, 389–413. https://doi.org/10.1146/annurev-vision-102016-061437

Hayhoe, M. M. (2018). Davida Teller Award Lecture 2017: What can be learned from natural behavior? *Journal of Vision*, *18*(4):10, 1–11, https://doi.org/10.1167/18.4.10. [PubMed] [Article]

Herwig, A., & Schneider, W. X. (2014). Predicting object features across saccades: Evidence from object recognition and visual search. *Journal of Experimental Psychology: General*, *143*(5), 1903–1922. https://doi.org/10.1037/a0036781

Heuer, A., Wolf, C., Schütz, A. C., & Schubö, A. (2017). The necessity to choose causes reward-related anticipatory biasing: Parieto-occipital alpha-band oscillations reveal suppression of low-value targets. *Scientific Reports*, *7*(1) , 14318.https://doi.org/10.1038/s41598-017-14742-w

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., Chelazzi, L., & Theeuwes, J. (2011). Reward has a residual impact on target selection in visual search, but not on the suppression of distractors. *Visual Cognition*, *19*(1), 117–128. https://doi.org/10.1080/13506285.2010.503946

Hickey, C., Chelazzi, L., & Theeuwes, J. (2014). Reward-priming of location in visual search. *PLoS One*, *9*(7),e103372. https://doi.org/10.1371/journal.pone.0103372

Hickey, C., & van Zoest, W. (2013). Reward-associated stimuli capture the eyes in spite of strategic attentional set. *Vision Research*, *92*, 67–74. https://doi.org/10.1016/j.visres.2013.09.008

Hox, J. (2002). *Multilevel analysis: Techniques and applications*. Mahwah, NJ: Erlbaum.

Jiang, Y., Song, J.-H., & Rigas, A. (2005). High-capacity spatial contextual memory. *Psychonomic Bulletin & Review*, *12*(3), 524–529. https://doi.org/10.3758/BF03193799

Lavie, N., & Dalton, P. (2014). Load theory of attention and cognitive control. In A. C. Nobre & S. Kastner (Eds.), *The Oxford handbook of attention* (pp. 56–75). New York: Oxford University Press.

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (2015). When goals conflict with values: counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of Experimental Psychology: General*, *144*(1), 158–171. https://doi.org/10.1037/xge0000037

Le Pelley, M. E., Seabrooke, T., Kennedy, B. L., Pearson, D., & Most, S. B. (2017). Miss it and miss out: Counterproductive nonspatial attentional capture by task-irrelevant, value-related stimuli. *Attention, Perception, & Psychophysics*, *79*(6), 1628–1642. https://doi.org/10.3758/s13414-017-1346-1

Le-Hoa Võ, M., & Wolfe, J. M. (2015). The role of memory for visual search in scenes. *Annals of the New York Academy of Sciences*, *1339*, 72–81. https://doi.org/10.1111/nyas.12667

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

Ludwig, C. J. H., Davies, J. R., & Eckstein, M. P. (2014). Foveal analysis and peripheral selection during active visual sampling. *Proceedings of the National Academy of Sciences of the USA*, *111*(2), E291–299. https://doi.org/10.1073/pnas.1313553111

Manginelli, A. A., & Pollmann, S. (2009). Misleading contextual cues: How do they affect visual search? *Psychological Research*, *73*(2), 212–221. https://doi.org/10.1007/s00426-008-0211-1

Olson, I. R., & Chun, M. M. (2001). Temporal contextual cuing of visual attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(5), 1299–1313. https://doi.org/10.1037/0278-7393.27.5.1299

Peterson, M. S., & Kramer, A. F. (2001). Attentional guidance of the eyes by contextual information and abrupt onsets. *Perception & Psychophysics*, *63*(7), 1239–1249. https://doi.org/10.3758/BF03194537

Pollmann, S., Eštočinová, J., Sommer, S., Chelazzi, L., & Zinke, W. (2016). Neural structures involved in visual search guidance by reward-enhanced contextual cueing of the target location. *NeuroImage*, *124*(A Pt), 887–897. https://doi.org/10.1016/j.neuroimage.2015.09.040

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Newbury Park, CA: Sage.

Schankin, A., Hagemann, D., & Schubö, A. (2011). Is contextual cueing more than the guidance of visual-spatial attention? *Biological Psychology*, *87*(1), 58–65. https://doi.org/10.1016/j.biopsycho.2011.02.003

Schankin, A., & Schubö, A. (2009). Cognitive processes facilitated by contextual cueing: Evidence from event-related brain potentials. *Psychophysiology*, *46*(3), 668–679. https://doi.org/10.1111/j.1469-8986.2009.00807.x

Schlagbauer, B., Geyer, T., Müller, H. J., & Zehetleitner, M. (2014). Rewarding distractor context versus rewarding target location: A commentary on Tseng and Lleras (2013). *Attention, Perception, & Psychophysics*, *76*(3), 669–674. https://doi.org/10.3758/s13414-014-0668-5

Schlagbauer, B., Müller, H. J., Zehetleitner, M., & Geyer, T. (2012). Awareness in contextual cueing of visual search as measured with concurrent access- and phenomenal-consciousness tasks. *Journal of Vision*, *12*(11) 25, 1–12, https://doi.org/10.1167/12.11.25. [PubMed] [Article]

Sharifian, F., Contier, O., Preuschhof, C., & Pollmann, S. (2017). Reward modulation of contextual cueing: Repeated context overshadows repeated target location. *Attention, Perception, & Psychophysics*, *79*, 1871–1877. https://doi.org/10.3758/s13414-017-1397-3

Simons, D. J., & Levin, D. T. (1997). Change blindness. *Trends in Cognitive Sciences*, *1*(7), 261–267. https://doi.org/10.1016/S1364-6613(97)01080-2

Smyth, A. C., & Shanks, D. R. (2008). Awareness in contextual cuing with extended and concurrent explicit tests. *Memory & Cognition*, *36*(2), 403–415. https://doi.org/10.3758/MC.36.2.403

Snijders, T., & Bosker, R. (1999). *Multilevel modeling: An introduction to basic and advanced multilevel modeling*. London: Sage.

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

Tan, M., & Wyble, B. (2015). Understanding how visual attention locks on to a location: Toward a computational model of the N2pc component. *Psychophysiology*, *52*(2), 199–213. https://doi.org/10.1111/psyp.12324

Tatler, B. W., Hayhoe, M. M., Land, M. F., & Ballard, D. H. (2011). Eye guidance in natural vision: Reinterpreting salience. *Journal of Vision*, *11*(5):5, 1–23, https://doi.org/10.1167/11.5.5. [PubMed] [Article]

Thaler, L., Schütz, A. C., Goodale, M. A., & Gegenfurtner, K. R. (2013). What is the best fixation target? The effect of target shape on stability of fixational eye movements. *Vision Research*, *76*, 31–42. https://doi.org/10.1016/j.visres.2012.10.012

Tseng, Y.-C., & Li, C.-S. R. (2004). Oculomotor correlates of context-guided learning in visual search. *Perception & Psychophysics*, *66*(8), 1363–1378. https://doi.org/10.3758/BF03195004

Tseng, Y.-C., & Lleras, A. (2013). Rewarding context accelerates implicit guidance in visual search.

Attention, Perception, & Psychophysics, *75*(2), 287–298. https://doi.org/10.3758/s13414-012-0400-2

van Asselen, M., & Castelo-Branco, M. (2009). The role of peripheral vision in implicit contextual cuing. *Attention, Perception, & Psychophysics*, *71*(1), 76–81. https://doi.org/10.3758/APP.71.1.76

Wolf, C., Heuer, A., Schubö, A., & Schütz, A. C. (2017). The necessity to choose causes the effects of reward on saccade preparation. *Scientific Reports*, *7*(1), 16966. https://doi.org/10.1038/s41598-017-17164-w

Zellin, M., Mühlenen, A. von., Müller, H. J., & Conci, M. (2014). Long-term adaptation to change in implicit contextual learning. *Psychonomic Bulletin & Review*, *21*(4), 1073–1079. https://doi.org/10.3758/s13423-013-0568-z

Zhao, G., Liu, Q., Jiao, J., Zhou, P., Li, H., & Sun, H.-J. (2012). Dual-state modulation of the contextual cueing effect: Evidence from eye movement recordings. *Journal of Vision*, *12*(6):11, 1–13, https://doi.org/10.1167/12.6.11. [PubMed] [Article]

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Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts

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ABSTRACT

Recent work on contextual cueing has shown that reward can facilitate context learning, e.g., when salient but task-irrelevant context features signal reward magnitude. Whether task-relevant context features yield a similar facilitating effect is unclear. Also, emergence and persistence of context learning for contexts associated with different reward magnitudes remains unclear. The present study investigated whether reward increases the speed with which context learning emerges, resulting in an earlier but asymptotically similar contextual cueing effect, or whether reward persistently increases context learning, visible as a larger contextual cueing effect on an asymptotical level. Reward was associated to the predominant orientation of the L-distractors, and the number of context repetitions was increased considerably. Results showed contextual cueing, i.e., faster responses and fewer fixations in repeated compared to novel contexts for all reward magnitudes. Moreover, a high reward led to a more pronounced contextual cueing effect. We developed a model-based approach to explicitly assess the non-linear decline and asymptotic level of the response time curves and to quantify how they were altered by reward. A hierarchical Bayesian parameter estimation revealed that reward decreased the asymptotic level of the repeated contexts' response times. Our results therefore show that reward leads to a persistent advantage in contextual cueing rather than to earlier but asymptotically similar context learning.

1. Introduction

The visual system is characterized by limited processing capacity, and humans have to determine which visual information they want to select for attending; a mechanism referred to as selective visual attention. Although we face a massive amount of visual information every day in our daily routines, visual information fortunately comes in a highly structured way arranged in visual scenes (e.g., Võ, Boettcher, & Draschkow, 2019). As we encounter many similar scenes every day, we can form expectations about future visual input (Summerfield & de Lange, 2014). For example, based on previous encounters with similar visual scenes, we have learned that certain stimuli are more likely to appear at specific locations within this scene. This statistical learning (e.g., Goujon, Didierjean, & Thorpe, 2015; Theeuwes, 2018) provides knowledge that can be used to guide attention to relevant locations when we encounter similar visual contexts again.

Evidence for the use of repeated contextual regularities for guiding visual attention comes from studies using visual search paradigms. In a seminal study, Chun and Jiang (1998) conducted a visual search task in which participants searched for a T-shaped target among a spatial context configuration of L-shaped distractors. This context configuration either repeated throughout the experiment ("repeated context") or was generated randomly in each trial ("novel context"). Participants were able to exploit the repeated context information to increase task performance, although they were not able to distinguish explicitly between repeated and novel contexts after the experiment. Observers responded faster in repeated compared to novel contexts, a statistical learning effect which developed during the experiment. The authors concluded that participants used the context as a spatial cue for finding the target, as a particular repeated context configuration was consistently associated with the location of the contained target, and described the effect as contextual cueing (Chun, 2000; Chun & Jiang, 1998).

Eye movement studies suggest that the contextual cueing effect is due to more efficient attention guidance in repeated compared to novel contexts (e.g., Harris & Remington, 2017). Participants move their eyes more efficiently to the target in repeated contexts, as the number of fixations was reported to be smaller and scan paths were shorter in these configurations (Bergmann, Koch, & Schubö, 2019; Manginelli & Pollmann, 2009; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao

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et al., 2012). Faster responses were reported to correlate with fewer fixations, which indicate more efficient attention guidance to the target in repeated contexts (Harris & Remington, 2017).

In the past 20 years, much research has focused on factors modulating the contextual cueing effect (for a review, see Goujon et al., 2015), for instance, particular stimulus characteristics were reported to be detrimental or beneficial to contextual cueing. While distractor homogeneity increases context learning, presumably because it facilitates similarity-based distractor grouping (Duncan & Humphreys, 1989; Feldmann-Wüstefeld & Schubö, 2014), arranging distractors such that they form meaningful geometrical patterns can be detrimental to learning (Conci & von Mühlenen, 2009; Conci & von Mühlenen, 2011; Conci, Müller, & von Mühlenen, 2013).

1.1. Reward and contextual cueing

Also motivational value, i.e., reward, has been demonstrated to play an essential role for contextual cueing. Tseng and Lleras (2013) observed that repeated contexts to which a reward feedback was tied were learned faster than contexts not followed by reward feedback. They concluded that participants learned an association of reward and the particular repeated contexts and that this association facilitated the learning of repeated contextual regularities (see also Pollmann, Eštočinová, Sommer, Chelazzi, & Zinke, 2016; Schlagbauer, Geyer, Müller, & Zehetleitner, 2014; Sharifian, Contier, Preuschhof, & Pollmann, 2017).

A recent study from our lab used a new approach in which reward could be predicted from the context configurations in both repeated and novel contexts (Bergmann et al., 2019). Reward was associated with a task-irrelevant color signaling either low, medium or high reward magnitude. Half of the L-distractors were presented in this color, the other half was presented in gray, and the target was colored in half of the trials. Color was thus task-irrelevant, as it defined neither the target nor the correct response. However, the color enabled the prediction of the subsequent reward magnitude in both novel and repeated contexts. We observed that a color predicting high reward magnitude increased the response time benefit observed with repeated contexts. However, no effect of reward magnitude was observed in novel contexts. We concluded that the expectation of reward facilitated the learning of repeated contextual regularities but did not result in a general performance increase in visual search. Interestingly, while reward boosted contextual cueing for high reward contexts, contextual cueing was reduced or virtually absent in low and medium reward contexts. We concluded that observers had not enough capacity for learning all repeated contexts used in that experiment and that reward expectation led to a preferential allocation of learning resources to high reward contexts (see also Pollmann et al., 2016).

Although initially expected, we did not observe a response time benefit in novel contexts in that study. This might be because color was a task-irrelevant dimension in the task. Color did predict reward magnitude, but color did not help to find the target. The correct response was also independent of the color, as observers had to judge the orientation of the target for responding. Thus, neither focusing on the set of colored items (cf. Beesley, Hanafi, Vadillo, Shanks, & Livesey, 2018; Jiang & Leung, 2005) nor a general attentional weighting of the color dimension (cf. Krummenacher & Müller, 2012) would have been helpful for increasing task performance in novel contexts. However, associating reward to a task-relevant rather than irrelevant context feature might affect task performance also in novel contexts. This possibility is examined in the present study.

1.2. Persistence of reward effects in contextual cueing

When Tseng and Lleras (2013) first combined the contextual cueing paradigm with reward, they originally hypothesized that reward might affect contextual cueing in one of two ways. They suggested that either a high reward leads to a larger contextual cueing effect on an asymptotical level or, alternatively, high and low reward lead to comparable contextual cueing effects in the end of the experiment but contextual cueing emerges earlier in high reward than in low reward contexts. The authors reported evidence for the latter, that is, faster emerging contextual cueing in high reward contexts rather than an enlarged effect on an asymptotical level.

Subsequent studies generally replicated that reward can be beneficial for contextual cueing (Bergmann et al., 2019; Pollmann et al., 2016; Sharifian et al., 2017; only Schlagbauer et al., 2014 reported conflicting results). However, it appears that the results are inconclusive concerning Tseng and Lleras' initial hypotheses. On the one hand, the results of one study rather fit with Tseng and Lleras' interpretation, as high reward mainly increased contextual cueing at the beginning of the experiment (in "epoch 1", blocks 1–4) and a comparable contextual cueing effect was observed in low reward contexts towards the end (in "epoch 4", blocks 13–16; Sharifian et al., 2017). On the other hand, two studies reported that contextual cueing was generally increased in high reward contexts and could even be absent or largely reduced in low reward contexts throughout the entire experiment (Bergmann et al., 2019; Pollmann et al., 2016). These results rather suggest that contextual cueing is generally larger in contexts associated with high reward than in contexts associated with no or low reward. The previous results are inconclusive and, as in the study of Tseng and Lleras, the amount of context repetitions (with reward feedback) was also a little larger than in other studies, future work is needed that enlarges the amount of context repetitions. This research gap is addressed in the present study.

1.3. Rationale of the present study

The present study had two goals: First, associating reward with a task-relevant context feature in every trial, and second, investigating the persistence of reward effects in contextual cueing.

Previous results showed that reward did not affect task performance in novel contexts when it was associated with a task-irrelevant context feature (Bergmann et al., 2019). However, associating reward with a task-relevant context feature, i.e., item orientation, might affect performance also in novel contexts, as participants process task-relevant features in these contexts as well. We therefore associated reward magnitude with the predominant distractor orientation in both repeated and novel contexts, enabling participants to predict the reward magnitude from the distractors in every trial. Item orientation is task-relevant because the task requires participants to search for the target (that is, the only item possessing the target-defining T-junction), and to identify the target item's orientation for responding. Thus, although item orientation cannot be used to search for targets, participants had to process item orientation for responding. Participants might therefore prioritize processing distractor orientations that are associated with a high reward both in repeated but also in novel contexts. We expected to observe a performance increase, i.e., shorter response times and more efficient eye movements to the target, in both repeated and novel contexts associated with high reward.

Former studies on reward in contextual cueing observed that contextual cueing can be absent or largely reduced in contexts associated with a low reward magnitude, probably because resources for context learning are limited and preferably allocated to high reward contexts (Bergmann et al., 2019; Pollmann et al., 2016). Up to now, however, it was not examined whether the contextual cueing advantage in high reward contexts persists over an extended amount of context repetitions. It might be possible that, after a larger amount of context repetitions, low reward contexts "catch up" and lead to contextual cueing effects of similar size (cf. Tseng & Lleras, 2013). Alternatively, high reward might persistently strengthen contextual cueing, visible in a larger contextual cueing effect in high reward contexts that persists also after many context repetitions.

To investigate these alternatives we conducted a contextual cueing experiment that comprised 48 repetitions for each repeated context over a two-day session. In addition, we used contexts known to require less capacity in learning. In contrast to previous studies on reward and contextual cueing, our contexts were comparably homogeneous, because most of the distractors were presented in the same orientation. Since homogeneous distractor orientations are reported to increase contextual cueing probably due to spontaneous grouping and less required capacity in memory (Feldmann-Wüstefeld & Schubö, 2014), we expected that participants had enough capacity to learn repeated contexts of all reward magnitudes (see also Jiang, Song, & Rigas, 2005).

We implemented a two-step approach for analyzing the persistence of reward effects in contextual cueing. First, we ran a linear mixed model analysis, which estimated linear slopes. This analysis allowed examining the effects of reward on the decline of RTs with minimalistic assumptions about the shape of the RT curves. In a second step, we applied a learning curve model with a learning rate parameter and an asymptotic performance parameter. This analysis aimed on teasing out further details about how both, learning rate and asymptote of the RT curves were modulated by reward. If reward modulates the slope mainly at the beginning of the curve, this should be reflected in the learning rate parameter. If reward persistently strengthens contextual cueing even after many context repetitions, this should be visible in the asymptotic performance parameter.

2. Method

2.1. Participants

We recruited 30 participants (14 female) taking part for payment or course credit. The participants were 19–29 years old ($M = 23.6$, $SD = 3.05$) and were neither familiar with the paradigm nor with the objective of the study. Everyone had normal visual acuity, tested with an Oculus Binoptometer 3. Each participant provided written consent in line with the ethical standards of the Declaration of Helsinki. The local Ethics Committee (Faculty of Psychology, Philipps-University Marburg) approved the experiment.

2.2. Apparatus

The participants took a seat in a sound attenuated and dimly lit room and placed their heads on a chinrest facing screen center. They responded with a gamepad (Microsoft Xbox 360 Gamepad). Stimuli were presented on an LCD-IPS screen (Cambridge Research Systems, Display++ LCD Monitor 32″, 1920 × 1080 pixels, 120 Hz) placed 100 cm in front of the participants. We recorded eye movements of the participants' right eye using an Eylink 1000 Plus desktop mounted eye tracker (SR Research Ltd., spatial resolution 0.01°, sampling rate 1000 Hz, calibrated with 13-point calibration procedure). A Windows 7 PC running E-Prime Professional (2.0.10.356) routines was used for response collection and stimulus presentation.

2.3. Stimuli

The search display was always composed of 16 items, 15 L-shaped distractors and 1 T-shaped target. All items were gray (RGB 128, 128, 128; 56.75 cd/m^2) presented on a dark gray background (RGB 64, 64, 64; 28.23 cd/m^2) and distributed on an imaginary 12 × 7 grid (35.5° × 20.7°). The L-shapes were either rotated 0°, 90°, 180°, or 270° and the T-shape was left-tilted or right-tilted. The L-shapes and T-shapes were equal in size (1.4° × 1.4°) and presented with a minimum distance of 1.7° between two items. The target appeared in one of four possible locations. One target location was placed in each quadrant of the screen with a two-cell distance to the grid's edges (11.3° eccentricity from screen center, Fig. 1B). Seven distractors were placed randomly on the target's side of the display, eight on the other side. Twelve distractors (80%) were rotated in the same orientation, the remaining three distractors in one of the other three orientations. All contexts were generated individually for each participant.

2.4. Procedure

Participants searched for the T-shaped target among context configurations of L-shaped distractors and reported whether the target was tilted to the left or right, which randomly varied in each trial. Half of the configurations repeated in each block ("repeated contexts"), the other half was generated newly for each trial ("novel contexts"). Participants received reward feedback (low, medium or high) for correct responses in both repeated and novel contexts. Crucially, the predominant distractor orientation was fully predictive of the reward magnitude they could achieve in each trial (Fig. 1B). Thus, as soon as participants learned the orientation-reward association, they were able to predict the reward from the distractors in both repeated and novel contexts. Participants were neither told that some contexts repeated nor that distractor orientation predicted reward.

2.4.1. Trial procedure (Fig. 1A)

A trial started with a fixation dot (Thaler, Schütz, Goodale, & Gegenfurtner, 2013) which was surrounded by a thin line and appeared at screen center. The participants had to fixate the fixation dot to start the trial. Then, the thin line around the dot disappeared and the search display was presented after 400 ms. Participants were asked to indicate the target orientation with one of two buttons on the gamepad's back and to respond as quickly but also as accurately as possible. The search display was shown until response or, after 1000 ms, replaced by a blank screen (shown for 600 ms). Next, point feedback was shown at screen center for 600 ms. Correct responses given within 1600 ms were rewarded (see Fig. 1B).

Incorrect and too slow responses (>1600 ms) were followed by "+0" feedback. The collected points were converted into a monetary bonus; 1000 points equaled 1 EUR, a maximum of 6.14 EUR could be achieved.

2.4.2. Experimental procedure

The experiment consisted of two sessions on separate days with a maximum of one day in between. Each session contained 24 blocks with 24 trials consisting of 12 repeated and 12 novel contexts presented in random order. Participants thus saw 48 repetitions of each context during the experiment. The number of context repetitions was thus doubled compared to our previous work (48 vs. 24; Bergmann et al., 2019) and the number of repeated contexts was halved (12 vs. 24). After each block, participants received feedback with mean response accuracy, mean response times, and the number of points they had already collected, followed by a pause of at least 10 s. At the beginning of session 1, participants performed two practice blocks containing only novel contexts and no reward to get familiar with the task. Participants directly started with the task in session 2 without additional practice. At the end of session 2, participants performed a recognition task. They were informed that some of the contexts had repeated during the experiment, and were confronted with the 12 repeated and another 12 novel contexts, presented in random order. Participants had to decide whether they had seen a context before. There were no time restrictions, we asked participants to decide intuitively. After the recognition task, participants filled a follow-up survey about individual search strategies and recognized experimental regularities. No participant reported having noticed that the predominant distractor orientation predicted reward magnitude.

3. Data analysis

To shed as much light as possible on the influence of reward on contextual cueing, we used a two-fold approach to analyze the

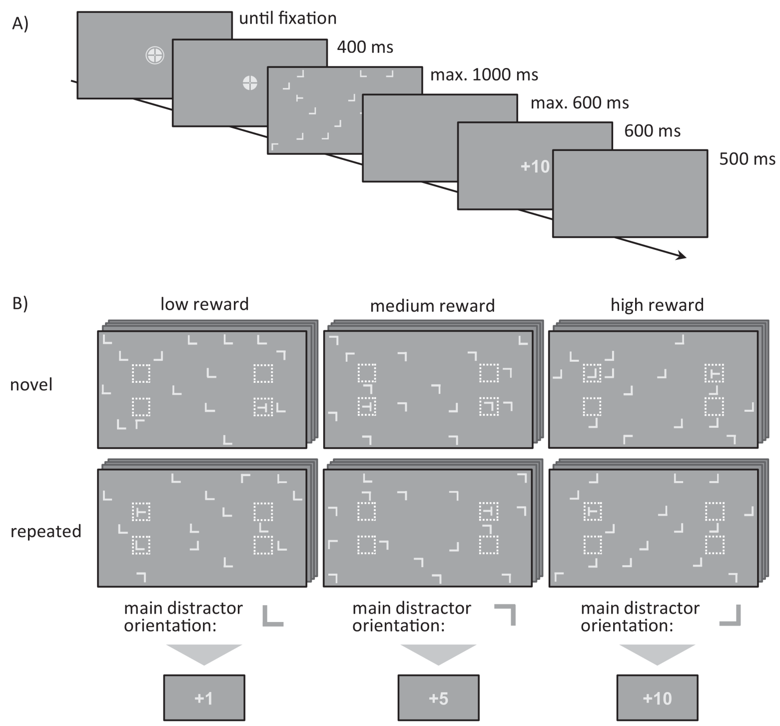

Fig. 1. Trial procedure of the contextual cueing task (A) and experimental design of the study (B). Participants searched the T-shaped target among L-shaped distractors and reported the target's orientation. Correct answers within 1600 ms after stimulus onset were rewarded. Reward magnitude depended on the predominant orientation of the distractors (B). The orientation-reward assignment was balanced across participants. The dotted squares (not visible in the experiment) indicate potential target locations. The same target locations were used for novel and repeated contexts and each reward magnitude.

experimental data. First, we applied a linear mixed model with a Frequentist evaluation. This part of the analysis aims to answer—with a minimum of assumptions—whether different levels of reward have an impact on how observers' performance improves with repeated contexts (modeled as differences in the slope of a linear decline in response times, error rates, and fixation count). The second part of the analysis is a Bayesian model comparison and parameter estimation approach. Here the goal is to incorporate prior knowledge about the shape of learning curves on the participant level and typical parameter ranges to tease out further details about how contextual cueing is altered by reward.

3.1. Mixed model analysis

3.1.1. Response times and error rates

Trials with response errors (5.6% of trials) and response times (RT) ± 2 *SD* from the mean RT of each participant in each block were excluded from the analysis (another 4.4% of trials). As contextual cueing is an effect that develops with each context repetition in the experiment, we applied a linear mixed model analysis for comparing the RT pattern in novel and repeated contexts across experimental blocks. As fixed effects, the model estimates a constant in block 1, which is identical in novel and repeated contexts because in block 1, all contexts are in fact "novel" to the participants. Starting from this constant, the model describes the decrease of RTs with each subsequent block by estimating slopes. The slopes of low reward contexts are considered the baseline (cf. Fig. 2, left), and the model compares the slopes of medium and high reward contexts with this baseline (cf. Fig. 2, middle and right panels). The model includes random intercepts and slopes. We report the estimated values of the model with the 95% confidence interval in square brackets. The mixed model calculates the estimates from the data based on single trials and was applied using IBM SPSS Statistics 25.

First, we applied the model to our complete data set, including both experimental sessions. In addition, we calculated the model separately for each session to examine to what extent contextual cueing and reward effects persisted across experimental sessions. Error rates were analyzed analogously.

3.1.2. Eye movements

Eye movement data was pre-processed using SR Research Data Viewer (Version 3.1.97) for extracting fixations, saccades, and blinks. We calculated the number of fixations (fixation count) until participants fixated an area with a diameter of 8.3° around the target location. The diameter of this area was chosen so that it included the cells next to the target in the grid. These cells were included because in some trials, participants did not directly fixate the target before responding although they were able to report the correct target orientation. The fixation count is considered a measure of the efficiency of attention guidance in visual search and has been frequently used in contextual cueing tasks (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012). For eye movement analyses, trials in which participants made response errors, blinked, started to move their eyes faster than 100 ms after stimulus onset or did not move their eyes were excluded (11.6% of trials). We only included trials in which the area of interest was fixated before giving a response (which removed the display), and before the display was removed automatically after 1000 ms (another 3.5% of trials removed). Data was submitted to the same mixed model as used for response times.

3.2. Bayesian model comparison and parameter estimation

For a closer investigation of how reward influenced the shape of the RT curves, we applied a hierarchical Bayesian model that at its core modeled the decline of RT over time with a learning curve (*LC*) with three free parameters:

$$RT(x) = \mathrm{LC}(x, s, c, a) = a + (s - a)x^{-c} \quad (1)$$

where $RT(x)$ is the response time in block x, a is the asymptotic RT

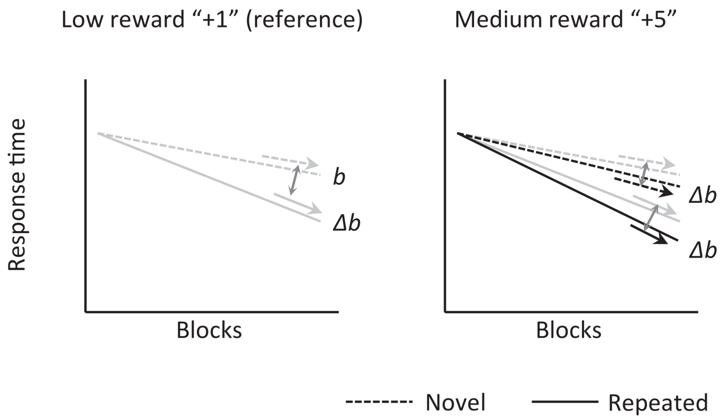

Fig. 2. Visualization of the calculated linear mixed model. As an anchor reference, the model estimates the slope of RTs in novel low reward contexts (b, dashed gray line, left panel), and estimates the difference between the slope of repeated low reward contexts and this anchor reference (Δb, solid gray line, left panel). The model also estimates the difference between the slopes of novel medium and novel low reward contexts (Δb, dashed black line, middle panel), and the difference between the slopes of novel high and novel low reward contexts (Δb, dashed black line, right panel). It also estimates the difference between the slopes of repeated medium and repeated low reward contexts and the difference between the slopes of repeated high and repeated low reward contexts (Δb, solid black lines, middle and right panels).

level toward which the curve levels off, and c is a learning rate parameter that determines the slope of the curve especially at its beginning. Parameter s is the starting RT level, that is, it represents the performance with which the participants start into the task. A learning curve of this type has been used to model contextual cueing effects, for instance, by Chun and Jiang (2003) with a slightly different parametrization. However, the equation above can be derived from the more commonly used form by substituting b (the range of improvement) with $(a - s)$. This has the benefit that the starting performance s can then be constrained to share a value across repeated and novel contexts and all reward levels. This expresses the assumption that for a given participant RTs in all conditions are the same at the beginning of the experiment when repeated contexts are equally new as novels and participants cannot yet recognize any relationship between the rewards.

We embedded this equation in a hierarchical Bayesian model that allowed for model comparisons (to determine whether reward influenced the learning rate parameter or the asymptotes) and parameter estimation; 32,000 Markov-chain Monte Carlos samples (across four chains) were obtained with NUTS ("No-U-Turn sampler"; see Hoffman & Gelman, 2014). The model comparison was conducted with leave-one-out (LOO) cross-validation based on Pareto-smoothed importance sampling (Vehtari, Gelman, & Gabry, 2017) as implemented in PyMC3 (Salvatier, Wiecki, & Fonnesbeck, 2016). The comparison considered four different cases:

1. Reward neither affects the learning rate parameter nor the asymptotes ("no effect")
2. Reward affects the learning rate parameter but not the asymptotes ("learning rate effect")
3. Reward affects the asymptotes but not the learning rate parameter ("asymptote effect")
4. Reward affects both asymptotes and learning rate parameter ("both effects")

We employed a two-stage procedure: first, model comparisons with these four alternatives were performed separately for novel and repeated contexts. The models with the best scores were then combined to provide a full model which was used for parameter estimation. In the combined model, the starting performance parameter s was shared between novel and repeated contexts (and among all reward conditions) as motivated above. The estimates obtained included basic parameters of learning curves (cf. Eq. 1) as well as estimates of the contextual cueing effect and the reward effects.

Details on the model structure can be found in Appendix A. The choices of priors are motivated in Appendix B along with visualizations of the information in the prior distributions relative to the posteriors. These show that estimates were governed by the data and not by the weak a priori information fed into the model.

For model comparisons, we report rankings based on LOO scores, estimates of their differences between models (dLOO) and estimates of the standard errors of these differences (dSE) and a relative weight for each model. Model parameter estimates are plotted as distributions or are given in textual form; we report the distribution modes and 95% Highest Probability Density intervals (HPDs).

3.3. Recognition task

Accuracy in the recognition task was analyzed with a repeated measures ANOVA with the two within-factors context type (novel vs. repeated) and reward (low vs. medium vs. high). Participants were similarly accurate in identifying repeated (M = 55% correctly identified contexts, SEM = 2) or novel contexts (M = 49%, SEM = 3), and the recognition accuracy did not differ between contexts with different reward magnitudes (all $ps \geq .124$).

4. Results

4.1. Mixed model analysis

4.1.1. Response times

Fig. 3 depicts response times (RT) in both experimental sessions. We first calculated the linear mixed model with the complete data set. The model estimated that in novel low reward contexts, RTs decreased by 1.4 ms with each block, $b = -1.4$ $[-2.0, -0.9]$, $t(33) = -5.04$, $p < .001$. The slopes of RTs in novel medium as well as novel high reward contexts did not differ significantly from the novel low reward contexts (novel low vs. medium reward: $\Delta b = -0.1$ $[-0.3, 0.1]$, $t(31048) = -0.95$, $p = .345$; novel low vs. high reward: $\Delta b = -0.04$ $[-0.23, 0.16]$, $t(31049) = -0.37$, $p = .713$). The slope of RTs in the

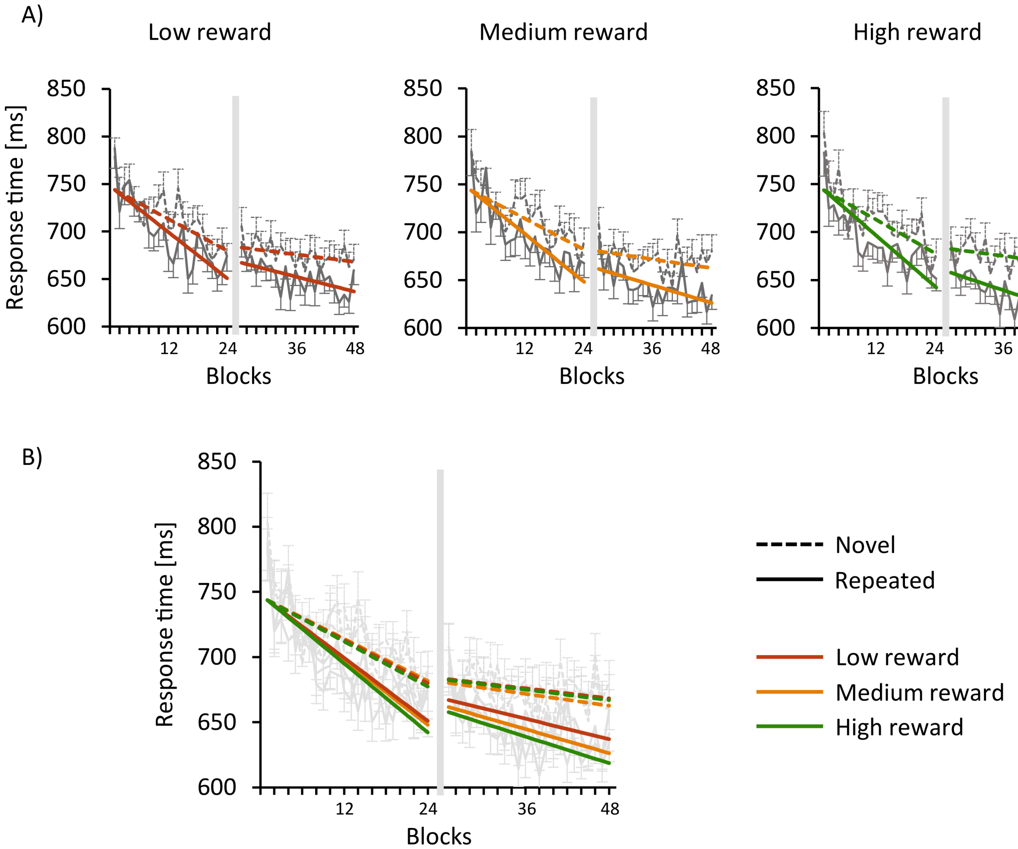

Fig. 3. (A) Response times in the course of the experiment. Response times are depicted separately for novel (dashed lines) and repeated contexts (solid lines) and for contexts associated with low reward ("+1", left panel), medium reward ("+5", middle panel), and high reward ("+10", right panel). The observed response times are shown as gray lines, the estimated slopes of the mixed models as colored lines. The gray bar stands for the time gap (maximum 1 day) between both experimental sessions. (B) depicts the same data as (A), but plotted in a single panel. Error bars show the standard error of the mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

repeated low reward contexts was significantly steeper than in the novel low reward contexts. The model estimated that the slope was 0.7 ms steeper indicating that repeated contexts' RTs decreased faster than novel contexts' RTs with each block, novel vs. repeated low reward: $\Delta b = -0.7$ $[-0.9, -0.5]$, $t(31048) = -7.35$, $p < .001$. The slope of repeated medium reward contexts did not differ significantly from repeated low reward contexts, $\Delta b = -0.1$ $[-0.4, 0.2]$, $t(31048) = -0.89$, $p = .374$. In repeated high reward contexts, in contrast, the slope was 0.4 ms steeper than in repeated low reward contexts, $\Delta b = -0.4$ $[-0.6, -0.1]$, $t(31048) = -2.52$, $p = .012$. These results indicate that RTs decreased faster in repeated compared with novel contexts with each block and that RTs decreased the fastest in repeated high reward contexts.

To quantify context learning in low, medium, and high reward contexts separately, we calculated additional mixed models for each reward magnitude. These models only included the slope of novel contexts and the difference of the repeated contexts' slope compared to the novel contexts (Δb, see Fig. 2, left panel), since each reward magnitude was evaluated separately. The slope of RTs was significantly steeper in repeated compared to novel contexts for all reward magnitudes: low, $\Delta b = -0.73$ $[-0.93, -0.53]$, $t(10332) = -7.31$, $p < .001$, medium, $\Delta b = -0.85$ $[-1.05, -0.65]$, $t(10321) = -8.46$, $p < .001$, high reward, $\Delta b = -1.09$ $[-1.28, -0.89]$, $t(10278) = -11.04$, $p < .001$. These results show that context learning was present in contexts of all reward magnitudes.

To examine whether context learning and reward effects changed across experimental sessions, we additionally calculated the mixed model separately for session 1 and 2 (see Fig. 3 for the estimated slopes of these separate models). In session 1, the model again estimated steeper slopes of RTs in repeated low reward than in novel low reward contexts, $\Delta b = -1.3$ $[-1.9, -0.7]$, $t(15166) = -4.19$, $p < .001$. Reward, however, had no effect on slopes in session 1 ($ps \geq .528$). In session 2, the slopes of novel low reward contexts missed significance indicating that the RTs had reached an asymptote and did not decrease further in session 2, $b = -0.6$ $[-1.6, 0.3]$, $t(31) = -1.34$, $p = .191$. In repeated low reward contexts, in contrast, RTs decreased also in session 2, $\Delta b = -0.7$ $[-0.9, -0.5]$, $t(15824) = -6.65$, $p < .001$. Importantly, the estimated slope of repeated high reward contexts was significantly steeper than in repeated low reward contexts, $\Delta b = -0.4$ $[-0.6, -0.1]$, $t(15824) = -2.56$, $p = .010$. No other effects were observed in session 2 ($ps \geq .233$). In sum, the separate analysis of both sessions revealed that RTs decreased faster in repeated compared with novel contexts in both sessions. In session 1, contexts associated with different reward magnitudes did not differ, whereas in session 2, high reward speeded RTs in repeated contexts.

Next, we analyzed the error rates. The linear mixed model applied

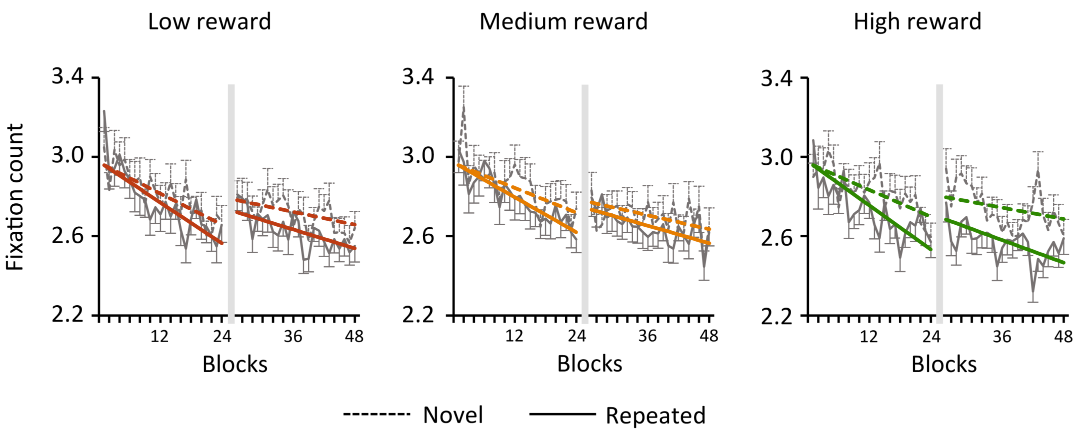

Fig. 4. Fixation count in the course of the experiment. The fixation count is depicted separately for novel (dashed lines) and repeated contexts (solid lines) and for contexts associated with low reward ("+1", left panel), medium reward ("+5", middle panel), and high reward ("+10", right panel). The observed fixation count is shown as gray lines, the estimated slopes of the mixed models as colored lines. The gray bar stands for the time gap (maximum 1 day) between both experimental sessions. Error bars show the standard error of the mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

to the complete data set estimated that participants started with an error rate of 10% in block 1, $b = 10.14$ [7.87, 12.42], $t(30) = 9.10$, $p < .001$. The model estimated that in novel low reward contexts, error rates improved by 0.17% with each subsequent block, $b = -0.17$ [−0.23, −0.12], $t(39) = -6.23$, $p < .001$. Slopes in repeated low reward contexts were estimated steeper, decreasing by 0.05% faster with each block, $\Delta b = -0.05$ [−0.08, −0.02], $t(34500) = -2.99$, $p = .003$. Slopes of both, novel and repeated high or medium reward contexts did not differ significantly from low reward contexts (all $ps \geq .071$). When we applied the mixed model to both sessions individually, the same pattern of results was visible in both sessions. In sum, participants made fewer errors in repeated compared with novel contexts and this effect developed as the experiment progressed. Reward magnitude had no significant influence on the error rates.

4.1.2. Fixation count

Fig. 4 depicts the average fixation count during the experiment. Similar to the response times, we first calculated the mixed model using the data from both experimental sessions. In novel low reward contexts, the model estimated that the average fixation count decreased by 0.005 with each subsequent block, $b = -0.005$ [−0.007, −0.003], $t(42) = -5.14$, $p < .001$. In repeated low reward contexts, the model again estimated a steeper slope and the fixation count decreased on average by 0.003 faster than in novel low reward contexts, $\Delta b = -0.003$ [−0.004, −0.002], $t(29287) = -4.56$, $p < .001$. The fixation count also decreased faster in repeated high reward contexts compared with repeated low reward contexts, $\Delta b = -0.002$ [−0.004, −0.001], $t(29287) = -2.67$, $p = .008$, while the slopes of repeated medium and repeated low reward contexts did not differ significantly, $\Delta b = 0.0009$ [−0.0008, 0.0025], $t(29287) = 1.06$, $p = .290$. Also the slopes of novel contexts associated with different reward magnitudes did not differ significantly (all $ps \geq .216$).

When we applied the model separately for both experimental sessions, the results mimicked the pattern of the RTs (see Fig. 4 for the estimated slopes of these separate models). The fixation count decreased faster with each block in repeated than in novel contexts in both sessions, session 1: $\Delta b = -0.004$ [−0.008, −0.001], $t(14156) = -2.29$, $p = .022$, session 2: $\Delta b = -0.003$ [−0.004, −0.001], $t(15077) = -4.16$, $p < .001$. Distractor orientations signaling high reward magnitude speeded the fixation count further, yet only in session 2 and only in repeated but not in novel contexts, $\Delta b = -0.002$ [−0.0038, −0.0004], $t(15076) = -2.48$, $p = .013$.

4.2. Bayesian model comparison and parameter estimation

4.2.1. Model comparisons

As outlined in Section 3.2, we first compared the four versions of the model ("no effect", "learning rate effect", "asymptote effect", "both effects") on the data from the novel contexts. The outcome of the comparison is listed in Table 1.

The "no effect" model reached the highest rank in the comparison based on response time data from the novel contexts, indicating that reward did not influence performance here. A different ranking was revealed when repeated contexts were submitted to the same model comparison (see Table 2). For the repeated contexts, the model that accommodated the differences in the RT curves in their asymptotes reached the highest rank. Here, the model with no effect (which ranked highest for the novel contexts) fell to the lowest rank. In sum, the model comparisons suggest that reward affected neither asymptotes nor learning rates of the novel contexts' RT curves and that reward modulated the asymptotes of the repeated contexts' curves.

4.2.2. Parameter estimates and contextual cueing effects

Based on the outcomes of the model comparisons reported above, we combined the "no effect" model for novel contexts with the "asymptote effect" model for the repeated contexts for parameter estimation. In doing so, we used a shared *s* parameter (starting performance) as motivated in Section 3.2, while all other common parameters were free to vary between the context conditions.

Table 1
Model comparison based on the novel contexts. Ordered from best (Rank 1) to worst (Rank 4).

Model	Rank	LOO	pLOO	dLOO	dSE	Weight
no effect	1	−17026.86	104.47	0.00	0.00	0.92
asymptote effect	2	−17009.47	131.93	17.39	11.99	0.08
learning rate effect	3	−16978.16	144.29	48.70	15.63	0.00
both effects	4	−16970.41	161.43	56.45	16.38	0.00

Note. Lower LOO scores indicate better models. pLOO is an estimate of the effective model parameters (hence it reflects parsimony); dLOO is the relative difference to the top-ranked model, and dSE an estimate of its standard error. "Weight" reflects the model's contribution if used in model averaging (it can be loosely interpreted as the probability of the model among the tested alternatives given the present data).

Table 2
Model comparison based on repeated contexts. Ordered from best (Rank 1) to worst (Rank 4).

Model	Rank	LOO	pLOO	dLOO	dSE	Weight
asymptote effect	1	−19891.52	152.03	0.00	0.00	0.69
learning rate effect	2	−19882.10	162.18	9.42	15.66	0.25
both effects	3	−19881.23	169.92	10.29	11.80	0.07
no effect	4	−19673.55	107.27	217.97	29.69	0.00

Note. For descriptions of the column headers, see Table 1.

Table 3 shows the parameter estimates of the full model applied to the data from novel and repeated contexts. Fig. 5A illustrates the mean predicted group-level RTs (based on the means of 50,000 posterior predictive samples drawn on the participant-level) as an overlay on the mean observed RTs. Fig. 5B depicts the contextual cueing effect at the end of the experiment (at block 48; *CC48*) predicted by the model (see Appendix A). It shows that RTs in the repeated contexts in all reward conditions differed substantially from RTs in the novel contexts (zero, no difference, is far outside of the 95% HPD). Panel 5C illustrates the effects of medium and high reward on the asymptotes of the RT curves relative to that of the low reward baseline. For medium reward, zero, no difference, was still within the 95% HPD. However, a large part of the distribution lies within the negative range (reduced asymptote). For high reward, zero, no difference, was clearly outside of the 95% HPD and in the negative range. This pattern is in agreement with the linear mixed-model analysis reported in Section 4.1 which suggested that a high reward led to a steeper slope in repeated contexts towards the end of the experiment (session 2). The parameter estimates of the learning curve model suggest that these "late" differences are due to a decreased asymptote of the RT curve in high reward repeated contexts.

5. Discussion

The present study investigated reward effects in contextual cueing. Reward magnitude was associated with a task-relevant context feature, in particular distractor orientation, to investigate reward effects in both novel and repeated contexts. In addition, we examined the persistence of reward effects. We examined whether a high reward magnitude resulted in a persistent advantage in contextual cueing even after many context repetitions or, alternatively, whether all reward magnitudes led to asymptotically similar contextual cueing effects. Participants searched through typical context configurations with half of the contexts repeating. In each context, 80% of the L-distractors shared the same orientation which served two purposes: First, the high context homogeneity facilitates context learning and thus contextual cueing in general (cf. Feldmann-Wüstefeld & Schubö, 2014). Second, the predominant distractor orientation enables the prediction of the reward magnitude in both repeated and novel contexts.

We observed contextual cueing, measured as faster responses in repeated compared to novel contexts, for all reward magnitudes. Faster response times in repeated contexts went along with a reduced number of fixations to the target (cf. Figs. 3 and 4). The more efficient eye movements suggest that the observed response time benefit was due to more efficient attention guidance to the target in repeated contexts (cf. Harris & Remington, 2017). Above that, the contextual cueing effect was largest when the predominant distractor orientation signaled a high reward. This was reflected in advantages in both response times and fixation count in repeated high compared to low reward contexts. Our study therefore adds to previous findings that associating a high reward with a context feature increases the contextual cueing effect (Bergmann et al., 2019).

5.1. *Persistence of reward effects*

Earlier studies observed that contextual cueing could be generally absent or largely reduced in contexts associated with a low reward magnitude (Bergmann et al., 2019; Pollmann et al., 2016). By contrast, the linear mixed model analysis in the present study showed that reward did not affect the linear RT slopes in session 1. This indicates that associating reward to distractor orientation did not immediately cause a strong prioritization of high reward contexts in context learning. Instead, similar contextual cueing was visible for high, medium, and low reward contexts. This suggests that observers had enough capacity to encode and learn all three repeated contexts, irrespective of the associated reward. Most likely, this was facilitated by the homogeneity of the contexts: as most of the distractors shared the same orientation, their similarity allowed for efficient perceptual grouping of context elements (see Duncan & Humphreys, 1989; Feldmann-Wüstefeld & Schubö, 2014). All studies reporting reward effects in contextual cueing used contexts that consisted of more heterogeneous distractor orientations (e.g., Sharifian et al., 2017; Tseng & Lleras, 2013). Heterogeneous context elements do not allow for spontaneous grouping, and therefore require more capacity for encoding and learning. As a result, participants had to prioritize context learning in these experiments.

Although reward did not strongly modulate task performance in session 1, reward effects manifested in session 2: High reward led to a more pronounced contextual cueing effect, visible in faster responses and more efficient eye movements (fewer fixations) in repeated high reward contexts. In addition, the learning curve model suggested that reward decreased the asymptote of the repeated contexts' RT curves. Hence, reward persistently boosted the contextual cueing effect, even after many context repetitions and even for contexts that require little encoding capacity and for which reward does not immediately prioritize learning (see also Chun & Jiang, 2003; Jiang et al., 2005).

5.2. *Learning rate and asymptote of the RT curves*

We examined the persistence of reward effects in contextual cueing by quantifying the shape of the RT curves. To this end, we aimed at disentangling how context novelty and reward affected the learning rate and the asymptotes of the curves. At this point, it is worth highlighting what differences in the asymptote and learning rate parameters actually mean to the individual shapes of the curves. Fig. 6 shows hypothetical learning curves with different asymptotes (left panel) and different learning rate parameters (right panel). Both, lower asymptotes as well as higher learning rate parameters lead to faster decreases at the beginning of the curve (see the blue boxes). Therefore, both, differences in the learning rates and in the asymptotes can be reflected in the development of early RTs. However, differences between both alternatives

Table 3
Group-level parameter estimates of the full model (novel and repeated contexts).

Contexts	s	c	a	a_{effect}
Novel (all rewards)	839 ms [796–902]	0.18 [0.12–0.26]	603 ms [502–681]	—
Repeated (low reward)	"	0.13 [0.10–0.16]	451 ms [321–556]	—
Repeated (medium reward)	"	"	"	−12 ms [−27 to 4]
Repeated (high reward)	"	"	"	−24 ms [−41 to −8]

Note. Square brackets indicate 95% Highest Probability Density intervals. Parameter s is the starting performance, c is the learning rate parameter, a the asymptotic RT level, and a_{effect} the reduction of the asymptotic RTs caused by reward.

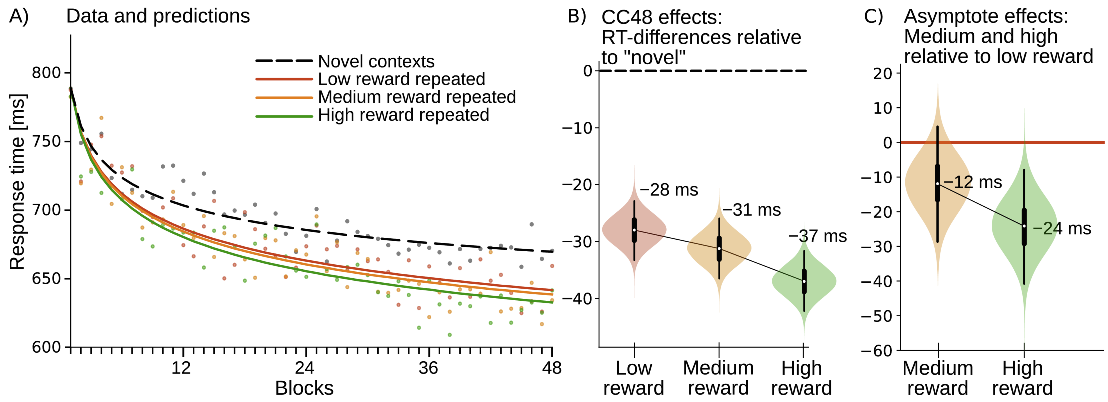

Fig. 5. (A) Mean RT curves predicted by the model (lines) and means of observed data (points; separately for each block). (B) Contextual cueing effect at the end of the experiment (CC48) and (C) effects of reward on the asymptotes estimated in repeated contexts with low reward as a baseline. The whiskers inside the distributions depict the 95% HPD interval, the thicker lines the 50% HPD interval, and the small white dots mark the modes of the distributions. The values of the modes are plotted next to the distributions.

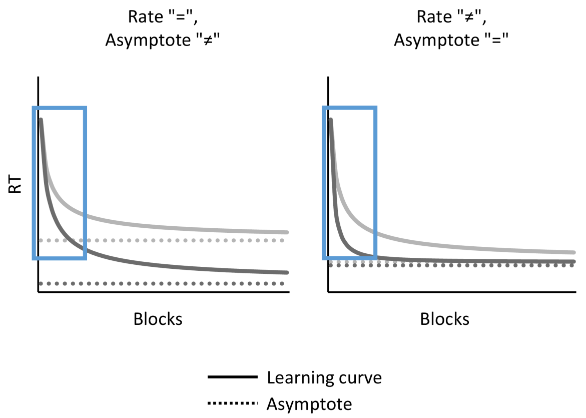

Fig. 6. Hypothetical learning curves (solid lines) with identical learning rates and different asymptotes (left panel) and identical asymptotes and different learning rates (right panel). The asymptotes are depicted as dotted lines. The blue boxes mark a time interval of the same length at the beginning of the hypothetical experiment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

manifest as the learning curves continue. Curves with identical learning rate parameters but different asymptotes converge to different RT levels as the curve continues (see left panel). That is, differences between the curves manifest toward the later blocks. Curves with the same asymptote but different learning rate parameters ultimately approach the same asymptote, with curves with higher learning rate parameters closing in earlier than curves with lower parameters (see right panel). That is, differences between these curves get smaller toward the later blocks.

5.2.1. Rate and asymptote in novel and repeated contexts

In the following, we first discuss differences in the asymptote and learning rate parameters between novel and repeated contexts. In the next section (5.2.2), the effects of reward on these parameters are discussed.

Our modelling results revealed that contextual cueing was expressed in different asymptotes of the RT curves. The estimated asymptotes were considerably lower in repeated compared to novel contexts, suggesting that differences between novel and repeated contexts manifested as the experiment progressed. We also observed a difference in the learning rate between novel and repeated contexts. Interestingly, the learning rate was *higher* in novel compared to repeated contexts (see Table 3). This means that the novel contexts not only had a higher asymptote than repeated contexts but that they also converged earlier toward it. This is consistent with the results of the linear mixed models. The linear slopes of novel contexts missed significance in session 2, which might indicate that they were close to reaching their asymptote in session 2 (see Fig. 3). In contrast, the curves of repeated contexts decreased further also in session 2, indicating that the curves were farer from convergence.

In sum, our results showed contextual cueing manifesting in faster RTs in repeated compared to novel contexts on an asymptotical level. We also found that novel contexts reached their asymptotical RT level earlier than repeated contexts. This is an interesting finding because earlier work, which used similar power functions to model contextual cueing RT curves, fixed asymptotes of novel and repeated contexts to a common value (e.g., Chun & Jiang, 2003; Goujon, Didierjean, & Marmèche, 2009). According to our findings, this might be inappropriate, since we observed clearly different asymptotes in novel and repeated contexts.

5.2.2. Reward reduced the response time asymptotes of repeated contexts

To investigate whether reward affected the RT asymptotes, the learning rate parameters, or both, we compared four different versions of the learning curve models that contained parameters for either of the effects, for both effects, or for no effect. This analysis was conducted separately for novel and repeated contexts (s. Tables 1 and 2). This model comparison revealed that reward influenced neither learning rates nor asymptotes in novel contexts. For repeated contexts, the "asymptote effect" model reached the best rank, suggesting that reward modulated the asymptote rather than the learning rate of the curves. We then combined the best models for repeated and novel contexts to estimate the learning rate parameters and the asymptotes in a subsequent step. The parameter estimates revealed that high reward led to increased differences between novel and repeated contexts on an asymptotical level by decreasing the asymptotes of the repeated contexts' curves (cf. Fig. 5C).

At first glance, our modelling results seem to contradict the interpretation of Tseng and Lleras (2013), who concluded that reward led to an earlier emerging but asymptotically similar contextual cueing effect. This view would go with an effect in the learning rate parameter rather than in the asymptotes of the curves (see Fig. 6, right panel). Tseng and Lleras compared the contextual cueing effect in repeated contexts followed by a reward feedback or no reward and observed that the rewarded contexts had a significantly larger contextual cueing effect already in the first epoch of their experiment. In the last epoch, the size of contextual cueing did not differ significantly between rewarded and non-rewarded contexts.

It is worth considering that our study differed in several aspects to Tseng and Lleras' study, which might complicate a direct comparison. First, the analysis method differed considerably. In the present study, we applied a learning curve model describing the shape of the RT curves, whereas Tseng and Lleras tested the effects of reward by comparing rewarded and non-reward contexts within separate epochs during the experiment. Possibly, the shape of their RT curves might also be well described by differences in the asymptotes rather than the learning rates of the curves. The observation of an early contextual cueing effect for rewarded contexts can be explained by both, asymptote and learning rate effects as demonstrated above (see the blue boxes in Fig. 6). Second, the present study used more context repetitions than Tseng and Lleras did. Response times of rewarded contexts might still have decreased with further context repetitions in Tseng & Lleras' study and an increased advantage of rewarded contexts might have emerged eventually.

Most importantly, however, we associated a *context feature* with reward in the present study enabling the prediction of reward in every context. Associating a reward with context features might affect learning rates and asymptotes in a different way than reward feedback without reward-predicting features present in every context. However, our results are not conclusive in this point. Future work needs to focus on the role of reward-predicting context features in the learning rates and asymptotes of the contextual cueing RT curves.

5.3. Reward effects in novel contexts

Associating reward with a task-relevant context feature did not affect response times in novel contexts in the present study. The linear mixed model did not reveal any differences in the linear slopes between novel contexts of different reward magnitudes (see Fig. 3B). Moreover, in the Bayesian model comparison the model with identical learning rates and asymptotes for all reward magnitudes scored best.

The logic of our design did not enable participants to associate reward with particular target locations, as the target locations were shared across all experimental conditions (see Fig. 1B). The predominant distractor orientation was thus predictive of the reward magnitude but did not inform about the target location. That reward could not be associated with specific target locations might explain why there was no effect for novel contexts. In earlier studies, reward was often paired with certain target locations in novel contexts (Pollmann et al., 2016; Schlagbauer et al., 2014; Sharifian et al., 2017). In these study designs, reward could principally increase task performance in novel contexts by increasing attentional weights at rewarded target locations (target location probability cueing, e.g. Jiang, Swallow, & Rosenbaum, 2013).

Although reward could not lead to a differential weighting of target locations in the present study, it could theoretically have influenced task performance also in novel contexts. In contrast to the studies described before, participants could predict the reward magnitude in repeated and novel contexts with display onset, which could entail general boosts of task motivation and consequently performance for higher rewards (Failing & Theeuwes, 2018). Nevertheless, our results suggest that reward affects task performance in contextual cueing only when participants can combine it with information predictive of the location of the target.

6. Conclusion

The present study shows that associating a reward to task-relevant context features increases contextual cueing persistently even after many context repetitions. The results suggest that reward-predicting stimuli can increase contextual cueing on an asymptotical level and can lead to more efficient attention guidance in repeated contexts signaling a high reward. The expectation of reward thus seems to influence how we process context information in our visual environment and how we rely on information acquired in former encounters with similar contexts.

CRediT authorship contribution statement

Nils Bergmann: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Jan Tünnermann:** Methodology, Software, Formal analysis, Writing - Review & Editing, Visualization. **Anna Schubö:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices A–C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.visres.2020.03.010.

References

Beesley, T., Hanafi, G., Vadillo, M. A., Shanks, D. R., & Livesey, E. J. (2018). Overt attention in contextual cuing of visual search is driven by the attentional set, but not by the predictiveness of distractors. *Journal of experimental psychology. Learning, Memory, and Cognition, 44*(5), 707–721. https://doi.org/10.1037/xlm0000467.

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision, 19*(3), 1–18. https://doi.org/10.1167/19.3.10.

Chun, M. M. (2000). Contextual cueing of visual attention. *Trends in Cognitive Sciences, 4*(5), 170–178. https://doi.org/10.1016/S1364-6613(00)01476-5.

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. *Cognitive Psyachology, 36*(1), 28–71. https://doi.org/10.1006/cogp.1998.0681.

Chun, M. M., & Jiang, Y. (2003). Implicit, long-term spatial contextual memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*(2), 224–234. https://doi.org/10.1037/0278-7393.29.2.224.

Conci, M., Müller, H. J., & von Mühlenen, A. (2013). Object-based implicit learning in visual search: Perceptual segmentation constrains contextual cueing. *Journal of Vision, 13*(3), 15. https://doi.org/10.1167/13.3.15.

Conci, M., & von Mühlenen, A. (2009). Region segmentation and contextual cuing in visual search. *Attention, Perception and Psychophysics, 71*(7), 1514–1524. https://doi.org/10.3758/APP.71.7.1514.

Conci, M., & von Mühlenen, A. (2011). Limitations of perceptual segmentation on contextual cueing in visual search. *Visual Cognition, 19*(2), 203–233. https://doi.org/10.1080/13506285.2010.518574.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review, 96*(3), 433–458. https://doi.org/10.1037/0033-295X.96.3.433.

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., & Schubö, A. (2014). Stimulus homogeneity enhances implicit learning: Evidence from contextual cueing. *Vision Research, 97*, 108–116. https://doi.org/10.1016/j.visres.2014.02.008.

Goujon, A., Didierjean, A., & Marmèche, E. (2009). Semantic contextual cuing and visual attention. *Journal of Experimental Psychology. Human Perception and Performance, 35*(1), 50–71. https://doi.org/10.1037/0096-1523.35.1.50.

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences, 19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009.

Harris, A. M., & Remington, R. W. (2017). Contextual cueing improves attentional guidance, even when guidance is supposedly optimal. *Journal of Experimental Psychology:*

Human Perception and Performance, 43(5), 926–940. https://doi.org/10.1037/xhp0000394.
Hoffman, M. D., & Gelman, A. (2014). The No-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research, 15*(1), 1593–1623.
Jiang, Y., & Leung, A. W. (2005). Implicit learning of ignored visual context. *Psychonomic Bulletin Review, 12*(1), 100–106. https://doi.org/10.3758/BF03196353.
Jiang, Y., Song, J.-H., & Rigas, A. (2005). High-capacity spatial contextual memory. *Psychonomic Bulletin Review, 12*(3), 524–529. https://doi.org/10.3758/BF03193799.
Jiang, Y. V., Swallow, K. M., & Rosenbaum, G. M. (2013). Guidance of spatial attention by incidental learning and endogenous cuing. *Journal of Experimental Psychology. Human Perception and Performance, 39*(1), 285–297. https://doi.org/10.1037/a0028022.
Krummenacher, J., & Müller, H. J. (2012). Dynamic weighting of feature dimensions in visual search: Behavioral and psychophysiological evidence. *Frontiers in Psychology, 3*, 221. https://doi.org/10.3389/fpsyg.2012.00221.
Manginelli, A. A., & Pollmann, S. (2009). Misleading contextual cues: How do they affect visual search? *Psychological Research Psychologische Forschung, 73*(2), 212–221. https://doi.org/10.1007/s00426-008-0211-1.
Peterson, M. S., & Kramer, A. F. (2001). Attentional guidance of the eyes by contextual information and abrupt onsets. *Perception and Psychophysics, 63*(7), 1239–1249. https://doi.org/10.3758/BF03194537.
Pollmann, S., Eštočinová, J., Sommer, S., Chelazzi, L., & Zinke, W. (2016). Neural structures involved in visual search guidance by reward-enhanced contextual cueing of the target location. *NeuroImage, 124*(Pt A), 887–897. https://doi.org/10.1016/j.neuroimage.2015.09.040.
Salvatier, J., Wiecki, T. V., & Fonnesbeck, C. (2016). Probabilistic programming in Python using PyMC3. *PeerJ Computer Science, 2*(2), e55. https://doi.org/10.7717/peerj-cs.55.
Schlagbauer, B., Geyer, T., Müller, H. J., & Zehetleitner, M. (2014). Rewarding distractor context versus rewarding target location: A commentary on Tseng and Lleras (2013). *Attention, Perception and Psychophysics, 76*(3), 669–674. https://doi.org/10.3758/s13414-014-0668-5.
Sharifian, F., Contier, O., Preuschhof, C., & Pollmann, S. (2017). Reward modulation of contextual cueing: Repeated context overshadows repeated target location. *Attention, Perception Psychophysics, 79*, 1871–1877. https://doi.org/10.3758/s13414-017-1397-3.
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.
Thaler, L., Schütz, A. C., Goodale, M. A., & Gegenfurtner, K. R. (2013). What is the best fixation target? The effect of target shape on stability of fixational eye movements. *Vision Research, 76*, 31–42. https://doi.org/10.1016/j.visres.2012.10.012.
Theeuwes, J. (2018). Visual selection: usually fast and automatic; seldom slow and volitional. *Journal of Cognition, 1*(1), 67. https://doi.org/10.5334/joc.13.
Tseng, Y.-C., & Li, C.-S. R. (2004). Oculomotor correlates of context-guided learning in visual search. *Perception and Psychophysics, 66*(8), 1363–1378. https://doi.org/10.3758/BF03195004.
Tseng, Y.-C., & Lleras, A. (2013). Rewarding context accelerates implicit guidance in visual search. *Attention, Perception and Psychophysics, 75*(2), 287–298. https://doi.org/10.3758/s13414-012-0400-2.
Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing, 27*(5), 1413–1432. https://doi.org/10.1007/s11222-016-9696-4.
Võ, M. L.-H., Boettcher, S. E., & Draschkow, D. (2019). Reading scenes: How scene grammar guides attention and aids perception in real-world environments. *Current Opinion in Psychology, 29*, 205–210. https://doi.org/10.1016/j.copsyc.2019.03.009.
Zhao, G., Liu, Q., Jiao, J., Zhou, P., Li, H., & Sun, H.-J. (2012). Dual-state modulation of the contextual cueing effect: Evidence from eye movement recordings. *Journal of Vision, 12*(6), 1–13. https://doi.org/10.1167/12.6.11.

Study III

Local and global context repetitions in contextual cueing: The influence of reward

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Abstract

Former work suggests that in contextual cueing, participants can use a repeating local context to learn to detect the target, yet most contextual cueing studies have relied on repeating global context properties. We examined whether observers can use local context repetitions in a similar manner as they use global context repetitions. In addition, we examined how reward-predicting context features modulate the use of local and global contexts. As features predicting high reward facilitate attention guidance in global contexts, they might also facilitate attention guidance in local contexts. Participants searched through contexts in which either the entire context configuration or only a local context around the target repeated, intermixed with novel contexts. Half of the items in every context appeared in a color signaling either low or high reward. We found that local context repetitions led to comparable benefits in response times and fixation count as global context repetitions did and, surprisingly, reward magnitude did not affect performance in local nor in global contexts. The results suggest that a local chunk of distractors can be used for context learning and attention guidance in a similar manner as the entire context configuration. Presumably, the high proportion of (partially) repeated contexts in the experiment contributed to the observed contextual cueing effect in both contexts.

Keywords: contextual cueing, local and global context repetitions, reward

Introduction

Unlike in many visual search tasks in the laboratory, visual information in our natural environment rarely comes arranged completely random. Instead, visual information is often arranged in a similar manner in similar contexts, which helps our visual system to quickly assess the situation and to decide what to do next. For example, when searching for particular objects in a kitchen scene (e.g., a sponge), we can use knowledge we have acquired in similar kitchen scenes for optimizing search (see Võ & Wolfe, 2012). For instance, we know that sponges are likely to appear near the sink in a kitchen because we frequently found sponges near sinks in the past. As a result, we can now use this information for guiding visual attention more efficiently to the target, that is, we look at the sink first. Similarly, observers were reported to use environmental regularities in visual search; for instance, they responded faster to targets appearing in high compared to low probability locations (Ferrante et al., 2018). This process of extracting statistical regularities from the environment is referred to as *statistical learning* (e.g., Ferrante et al., 2018; Goujon, Didierjean, & Thorpe, 2015; Theeuwes, 2018). Statistical learning helps organisms to overcome the problem of limited encoding capacity and facilitates focusing on locations that provide observers with relevant information (Li & Theeuwes, 2020; Theeuwes, 2018; Wang & Theeuwes, 2020).

One influential paradigm frequently used for investigating the statistical leaning of repeated contexts in visual search is *contextual cueing* (Chun, 2000; Chun & Jiang, 1998). In the original paradigm, participants search for a "T"-shape among distractor contexts of "L"-shapes. Unbeknown to the participants, half of these context configurations repeat in each experimental block, while the other half is generated randomly. Chun and Jiang (1998), who first reported the effect, observed that participants became faster in reporting the target in repeated contexts than in novel contexts – although they were unable to explicitly recognize repeated contexts after having performed the experiment. Studies using eye tracking in contextual cueing suggest that the faster responses are due to more efficient attention guidance to the target because not only response times get shorter in repeated contexts but also eye movements are guided more efficiently to the target (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012).

Learning of local and global context information

While there is growing evidence for more efficient attention guidance in repeated than in novel contexts, the mechanisms underlying this facilitation are less clear (see Goujon et al., 2015, for a review). One possibility is that observers implicitly learn a global representation of repeated contexts, that is, an association of the complete repeated distractor configuration and the location of the target. When the context reappears, observers might guide their attention to the target, based on this global representation.

There is empirical evidence that global characteristics of the search contexts are learned and linked to the target location. Kunar, Flusberg, and Wolfe (2006), for instance, observed that associating the background color of distractor contexts with particular target locations led to contextual cueing effects. In addition, there is evidence that participants learn associations between the different distractor elements irrespective of the enclosed target, which also speaks for global learning. When participants search through repeated contexts in which the distractor configuration remains invariant over trials but the target randomly changes its location, participants show increased contextual cueing when these contexts are consistently paired with a target location in a subsequent phase (Beesley, Vadillo, Pearson, & Shanks, 2015). Observers thus benefit from prior exposures to repeated contexts, even when associations with a certain target location were prevented at that time. These results suggest that global characteristics of the distractor context are encoded as part of contextual cueing.

On the other side, there is also evidence that observers might only learn a local chunk of information surrounding the target location, which might be sufficient for producing contextual cueing effects. Olson and Chun (2002), for instance, conducted a contextual cueing task in which they used four different context types. In addition to the usual repeated and novel contexts, the authors used contexts in which they only repeated a part of the displays in each block. They repeated either the left or the right side of the context, whereas the other side was generated newly in each trial. The target could either be contained in the repeated side of the display ("short-range context") or in the novel side ("long-range context"). The authors observed a response time benefit in completely repeated contexts compared to novel contexts, that is, the classical contextual cueing effect. However, when only the target's side of the display repeated and the other side was novel, the authors could also observe a response time benefit. Interestingly, this effect was absent when the target was placed in the novel side of the display. The authors concluded that the participants only learned a local context surrounding the target, and not a complete global representation of repeated contexts (see also Brady & Chun, 2007; Song & Jiang, 2005; Zang, Jia, Müller, & Shi, 2015). They further suggested that when the target appeared on the novel side, the separation of the target and repeated distractors by randomly generated items hindered the association of the repeated items and the target location.

The local context surrounding the target seems not only sufficient for contextual cueing to evolve, but it also determines whether contexts can be associated with a new target location after contextual cueing had already been established ("adaptation of contextual cueing", Annac, Conci, Müller, & Geyer, 2017). Previous studies had reported that contextual cueing was heavily impaired when the target was moved to a new location in repeated contexts after learning had already emerged, and that context learning only recovered slowly and with an extensive amount of context repetitions (e.g., Zellin, Mühlenen, Müller, & Conci, 2014). Annac and colleagues (2017) proposed that the item density in the target's local context might explain why adaptation of contextual cueing can be limited. They conducted a contextual cueing experiment with (global) repeated and novel contexts and observed a reliable contextual cueing effect after participants had performed 24 blocks. Thereafter, the target was moved to a new location in repeated contexts, while the repeating distractor configuration remained unchanged. This manipulation allowed examining whether contextual cueing adapted to the new location in two conditions: when the target moved to a location in which the local distractor context was arranged sparsely, with only one distractor in a local context patch surrounding the target, or when it moved to a dense local context patch of similar size with three distractors. For the sparse context patch, a reliable contextual cueing effect was observed across the blocks 25-48, but not for the dense context patch. Interestingly, however, responses were *faster* to targets in the dense compared to the sparse patch. The authors suggested that items in the dense target patches were spontaneously grouped (Duncan & Humphreys, 1989), and automatically caught the observer's attention. This facilitated target detection in the dense target patch, explaining the faster target responses, but grouping also hindered learning to associate the context with the new target location, because fast target detection reduced the time available for learning a new association. In a control experiment, the authors presented the target in either a dense or sparse local context patch right from the start of the experiment, without moving the target location. The results showed a contextual cueing effect for targets in patches with both densities. This finding suggests that the item configuration in local contexts can be crucial for learning a new association, especially when an association has already been established.

In sum, there is evidence for both mechanisms, learning of a global representation of repeated contexts as well as learning of a restricted local context surrounding the target. The question therefore arises which factors determine whether a repeated context is encoded in a local or a global fashion in contextual cueing.

Attention determines context learning

An important factor determining which parts of repeated contexts are learned in contextual cueing is attention (e.g., Jiang & Leung, 2005; see also Beesley, Hanafi, Vadillo, Shanks, & Livesey, 2018; Jiang & Chun, 2001; Jiang & Song, 2005). In their contextual cueing task, Jiang and Leung (2005) composed the search display of black and white distractors; the target was constantly white throughout the experiment (black for half of the participants; the following sentences apply to white targets). This manipulation separated the context into two sets. The set of white items always contained the white target among white distractors, whereas the set of black items never contained the target. The authors repeated either the complete display, or only the black, or only the white items, whereas the other set was generated newly in each trial. These completely or partly repeated contexts were presented among novel contexts in which both sets were generated newly. The authors observed reduced response times in completely repeated contexts and also in repeating white items contexts. When only the black items repeated, no response time benefit was found. The authors concluded that participants attended the white items only, as this set always contained the target. As a result, an association was only established for white item context and the target location. Because the black items seemed not relevant when searching for the target item, they were not attended, and even when black items repeated, an association between black context items and the target was not established.

Reward influences attention guidance in contextual cueing

Attention, crucial for contextual cueing, is susceptible to reward (for reviews, see Anderson, 2016; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Failing & Theeuwes, 2018; Theeuwes, 2018). Assigning reward increases the perceived visual salience of a stimulus (Hickey, Chelazzi, & Theeuwes, 2010) and reward can bias visual selection even against the observers' intentions (e.g., Feldmann-Wüstefeld, Brandhofer, & Schubö, 2016; Le Pelley, Pearson, Griffiths, & Beesley, 2015).

Also in contextual cueing, reward-predicting stimuli can influence attention guidance. Salient reward-predicting colors in the display were reported to lead to an increased contextual cueing effect and increased the efficiency of attention guidance in repeated contexts (Bergmann, Koch, & Schubö, 2019; for other studies on reward and contextual cueing, see Bergmann, Tünnermann, & Schubö, 2020; Pollmann, Eštočinová, Sommer, Chelazzi, & Zinke, 2016; Schlagbauer, Geyer, Müller, & Zehetleitner, 2014; Sharifian, Contier, Preuschhof, & Pollmann, 2017; Tseng & Lleras, 2013). Bergmann and colleagues (Bergmann, Koch et al., 2019) used a contextual cueing task in which half of the items were presented in one of three colors, whereas the other half was gray. The color was consistently associated with a reward feedback participants received for correct responses and present in both novel and (completely) repeated contexts. Thus, participants could predict the reward from the color with display onset. Results showed that a color signaling high reward decreased response times in repeated but not in novel contexts. High reward also led to more efficient eye movements: Participants made fewer fixations in repeated compared to novel contexts and the first fixation landed closer to the target in high reward trials – interestingly, only when the contained color predicted high but not medium or low reward. High reward thus increased task performance by facilitating attention guidance to the target in repeated contexts.

Rationale of the present study

In the present study, we investigated whether observers use local context repetitions in a similar manner as global context repetitions to detect the target, and whether colored stimuli signaling reward facilitate attention guidance in local context configurations in a similar manner as has been reported for global ones. If reward-predicting context features facilitate attention guidance in global contexts, they might also facilitate the use of local context repetitions. On the other side, it is also possible that reward does favor global more than local context configuration learning, because repeating only few items might not be sufficient to learn to guide attention to the target. To investigate these alternatives, we conducted a contextual cueing task using three context configuration types. We repeated either the complete global context configuration or only a local patch that surrounded the target and included three distractors – a number of context items that has been reported to be the minimum for successful context retrieval (Song & Jiang, 2005). These global repeated and local repeated contexts were randomly intermixed with novel contexts in each block. Half of the items in each context configuration type – global, local, and novel – were presented in a color that signaled a high or a low reward given for correct responses (cf. Figure 1).

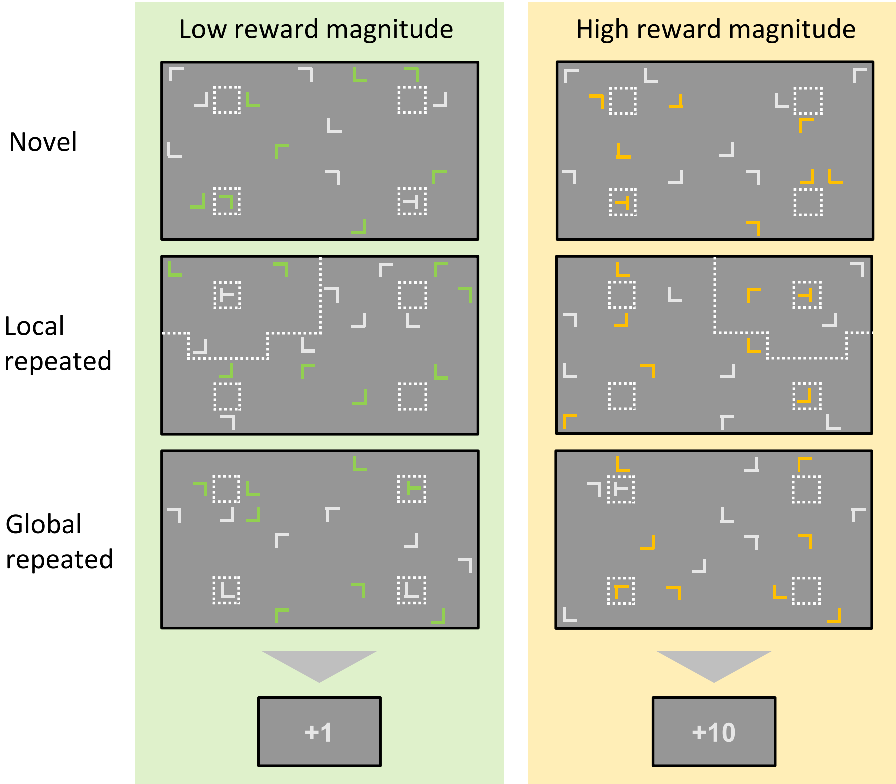

Figure 1. Exemplary search context configurations in novel (upper row), local (middle row), and global contexts (lower row) associated with low (left column) and high reward (right column). In global contexts, the entire context configuration repeated with each block. In local contexts, only a patch surrounding the target repeated (indicated by the dotted lines, not visible to participants). This patch always contained two colored and two gray items. In novel contexts, the entire context configuration was generated newly in each trial. The same four target locations were used for all context types (dotted squares, not visible to participants). The color-reward association was balanced across participants.

We expected that participants would show context configuration learning in global contexts and, presumably, also in local contexts, which should manifest in faster target response times in local and global compared to novel contexts. In addition, we examined whether observers benefited from a local context repetition in a similar manner as from global context repetitions. Since global contexts contained a good deal more repeating distractors as local contexts (15 vs. 3, see Figure 1), however, one may alternatively assume that target response times in global contexts are faster than response times for targets presented in local contexts. We also examined the number of fixations until the target was fixated, a measure which has been frequently related to the efficiency of attention guidance in contextual cueing (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004). If observers can use local contexts in a similar manner for finding the target as global ones, this should manifest in fewer fixations in local and global compared to novel contexts, which should be comparable for local and global contexts. If, however, participants use global contexts more than local ones for finding the target, one would expect to observe fewer fixations in global than in local contexts. Reward might boost context configuration learning, which should be visible in faster response times and fewer fixations for high compared to low reward contexts for both, local and global contexts similarly. If, however, reward facilitates learning of global context configurations more than for local contexts, a color signaling high reward should lead to larger reductions of responses times and fixation count in global than in local contexts.

Method

Participants

We recruited sixty volunteers (42 female; 18-30 years, *M* = 21.6, *SD* = 2.61) that participated for payment or course credit. All participants were naïve to paradigm and objective of the experiment, had normal or corrected-to-normal visual acuity, and showed no signs of color blindness (confirmed with Oculus Binoptometer 3). We removed one participant from the analyses because of high error rates (> 3 *SD* from the group mean). Before the experiment started, participants gave written consent in line with the ethical standards of the Declaration of Helsinki. The experiment was approved by the local Ethic Committee of the Faculty of Psychology at Philipps-University Marburg.

Apparatus

The participants were placed 100 cm in front of an LCD-IPS screen (Cambridge Research Systems, Display++ LCD Monitor 32", 1920 × 1080 pixels, 120 Hz) and responded with the buttons of a gamepad (Microsoft Xbox 360 Gamepad). Eye movements were recorded using an EyeLink 1000 Plus eye tracker (SR Research Ltd., spatial resolution 0.01°, sampling rate 1000 Hz). Head movements were prevented with a chin rest aligned to the center of the screen. The eye tracker was calibrated with the EyeLink 13-point calibration procedure. We used E-Prime Professional (2.0.10.356) routines for stimulus presentation and response collection.

Stimuli

The search contexts consisted of 15 L-shaped distractors and 1 T-shaped target, aligned on an invisible 12 × 7 grid (35.5° × 20.7°) with a minimum of 1.7° between two items. The distractors (L's) were rotated 0°, 90°, 180°, or 270° and the target (T) was tilted to either the left or right. All items were presented in the same size (1.4° × 1.4°). In every trial, the target appeared in one of four fixed locations, each located in one quadrant of the screen (12.4° eccentricity from screen center, cf. Figure 1). Of the 16 items, eight were gray (RGB 128, 128, 128; 56.75 cd/m^2) and eight were homogeneously colored. The background was dark gray (RGB 64, 64, 64; 28.23 cd/m^2). The search contexts were generated by randomly placing seven distractors on the target's side of the display and eight on the other side. We distributed the colored items equally to both sides of the display, four colored items on the left and four on the right side. The colored items were green (RGB 29, 173, 69; 56.65 cd/m^2) or orange (RGB 252, 104, 4; 56.78 cd/m^2), both colors were isoluminant to the gray items. The target was either gray or colored. We defined a 21-cell patch surrounding the target (cf. Figure 1). This patch always contained three distractors and the target. Two items within the patch were always colored and two were gray. The target patch covered one quarter of the grid's cells (21 of 84) and contained one quarter of the items (4 of 16). All contexts were generated individually for each participant.

Procedure

Trial procedure. Participants started the trial by fixating a fixation dot (Thaler, Schütz, Goodale, & Gegenfurtner, 2013) shown at screen center. The dot was surrounded by a thin line, which disappeared when the dot was fixated. After 400 ms, the search display was shown. Participants were asked to press one of two buttons on the gamepad's back to indicate the orientation of the target, which varied randomly in each trial. The search display was removed with response, or replaced by a blank screen after 1000 ms. After the response, the achieved reward points were shown at screen center for 600 ms. When participants responded correctly within the time limit of 1600 ms, they were rewarded with "+1" or "+10" points, which depended on the color contained in the search display (see Figure 1). They received "+0" feedback after incorrect responses or responses slower than 1600 ms. We instructed participants that they could earn points for responding correctly but we did not inform them that color predicted the reward magnitude. We converted the collected points into a monetary bonus (max. 5.28 EUR).

Experimental procedure. The experiment consisted of two sessions on separate days (max. one day in between). Session 1 contained 12, session 2 contained 8 blocks with 48 trials each. Within each block, 16 global contexts, 16 local contexts, and 16 novel contexts were presented in random order. In global contexts, the entire context configuration repeated with each block. In local contexts, only the patch surrounding the target repeated, whereas the remaining context configuration was generated newly in each trial. In novel contexts, the entire context configuration was generated newly in each trial. Half of all contexts in each context configuration type – global, local, and novel – contained the color signaling high, the other half the color signaling low reward (cf. Figure 1). Individual configurations were generated for contexts containing a colored and contexts containing a gray target so that half of all contexts contained a colored and the other half contained a gray target. The first experimental session started with one block of practice trials. The practice contained only novel contexts without reward feedback. The block was repeated if participants did not reach an average response accuracy of at least 65 %. After each experimental block, participants received performance feedback (mean response accuracy, mean response time, amount of points they had collected). After the block feedback, participants made a short pause of at least 10 seconds.

Data analysis

Response times and error rates. For response time (RT) analyses, we removed all trials with incorrect or too slow responses (12 % of trials) and all trials exceeding ± 2 *SD* from the mean of each participant in each block (another 3 %). The remaining RTs were collapsed for each participant and block, separately for each context type and each reward magnitude. The error rates were aggregated like the RTs.

Eye movements. We extracted fixations, saccades, and blinks using SR Research Data Viewer (Version 3.1.97). As for RT, we analyzed only trials with correct responses. In addition, we removed trials without eye movements, with blinks, and in which participants moved their eyes faster than 100 ms after stimulus onset (another 9 % of trials removed). We then calculated the number of fixations (fixation count) until a fixation landed in an area of 8.3° around the target location. This area also included the cells next to the target, since in some trials participants responded correctly although they had not fixated the target directly. Only trials in which participants reached the area during display presentation were used and the fixation count was aggregated like RTs and error rates. All analyses were calculated using IBM SPSS Statistics 25.

Recognition task. After the main experiment, participants performed a recognition task consisting of one block (48 trials). Participants encountered the 16 global, 16 local, and 16 novel contexts in random order and decided for each context whether they had seen it before or whether it was novel. Before the task started, we informed the participants that some of the contexts were repeating during the experiment. We however did not reveal that, in some trials, only the target patch repeated. There was no time restriction for this task.

Accuracy in the recognition task was analyzed using a repeated measure ANOVA with the factors *context type* (novel vs. local vs. global) and *reward* (low vs. high). The recognition accuracy was higher in global and local contexts compared to novel contexts, indicated by a main effect of context type, $F(1, 80) = 8.84$, $p = .001$ (Greenhouse-Geisser corrected), $\eta^2_p = .132$. Pairwise comparisons based on estimated marginal means confirmed that the accuracy was significantly lower in novel ($M = 45$ % correctly identified contexts, $SEM = 2$) than in local ($M = 56$ %, $SEM = 2$), $p = .009$, or in global contexts ($M = 57$ %, $SEM = 2$), $p = .006$. The recognition accuracy in local and global contexts did not differ significantly, $p = 1$ (p-values are Bonferroni corrected). The main effect of reward missed significance, $F(1, 58) = 3.33$, $p = .064$, and also the interaction was not significant, $F(1, 116) = 0.29$, $p = .751$. These results indicate that the recognition accuracy was increased for both local and global contexts, whereas both did not differ significantly from each other.

Results

To quantify context learning in local and global contexts, we calculated a linear mixed model analysis. The mixed model estimates the response times (RT) in block 1 as a constant. This value is identical for all context configurations, since at the beginning of the experiment, all contexts are "novel" to the participants. The model describes the decline of RTs by estimating slopes. The slope of RTs in novel contexts is used as a reference for comparisons with the slopes in local and global contexts. A steeper slope in local or global compared to novel contexts indicates that context learning emerges, i.e., RTs decrease more in these contexts than in novel contexts. To examine whether reward facilitated learning of local and global context configurations in a similar manner, the model investigates potential modulations of reward magnitude on the slopes by using low reward as the reference. The model estimates the difference of the slopes in high reward compared to low reward contexts, separately for novel, local, and global contexts. In the following, we report the estimated values of the model (95 % confidence interval in square brackets). The model includes random intercepts and slopes and the identical mixed model was applied to the error rates and fixation count.

Response times

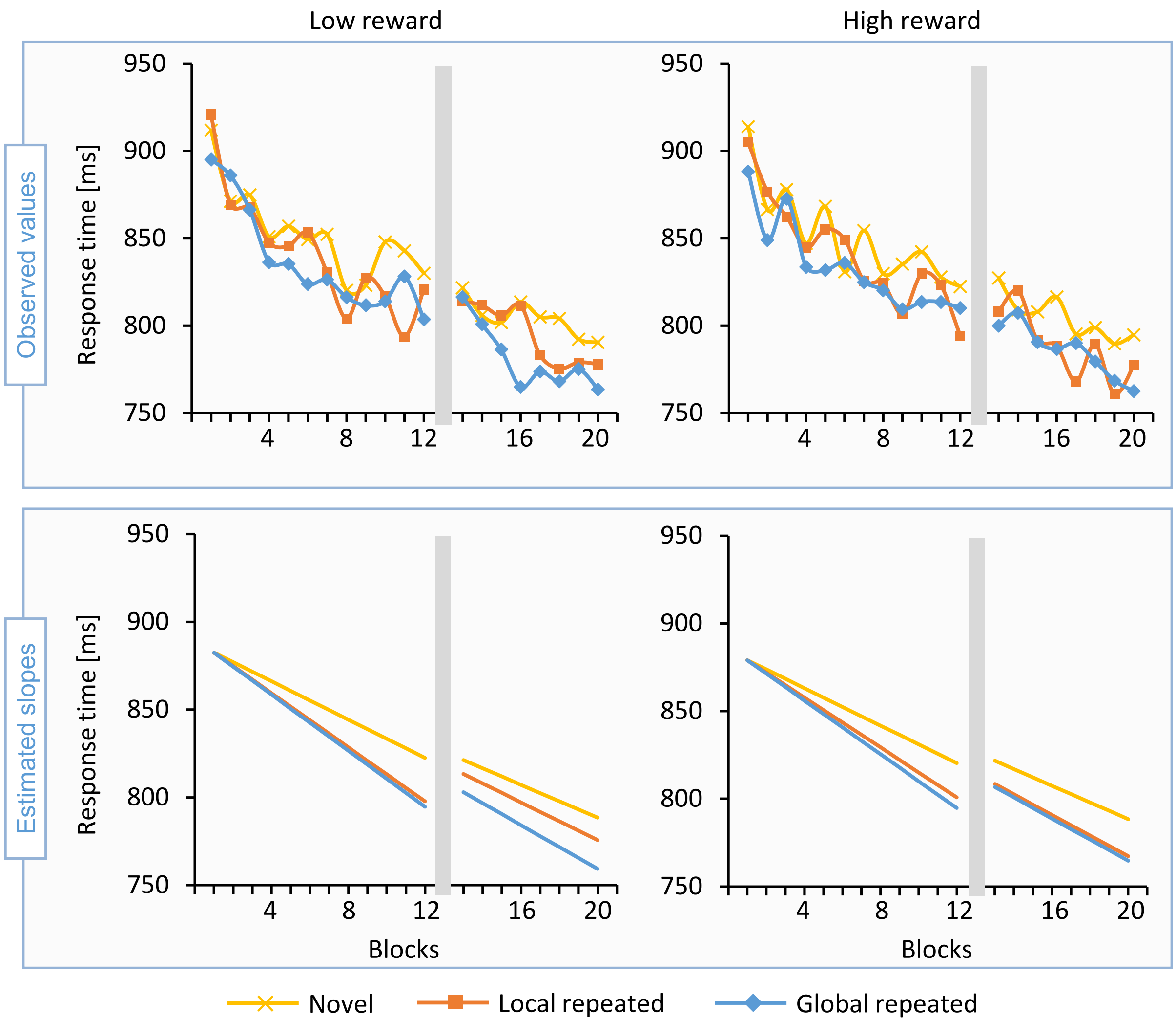

Figure 2. Response times observed during the experiment (upper panels) and estimated slopes of the mixed models (lower panels). Separate panels depict RTs for low (left column) and high reward (right column). RTs measured for novel contexts are shown as yellow, RTs for local contexts as orange, and for global contexts as blue lines. The gray bar stands for the time gap between the sessions.

The observed RTs are depicted in Figure 2, upper panels. The mixed model estimated that RTs decreased by 4.5 ms with each block in novel contexts, $b = -4.5$ [−5.6, −3.4], $t(75) = -8.09$, $p < .001$. The slope in global contexts was estimated 1.7 ms steeper, $\Delta b = -1.7$ [−2.3, −1.2], $t(6962) = -6.00$, $p < .001$. Also the slope in local contexts was estimated steeper than the slope in novel contexts, but the difference was estimated only 1 ms, $\Delta b = -1.0$ [−1.6, −0.4], $t(6962) = -3.43$, $p = .001$. These results indicate that RTs decreased faster in both local and global contexts than in novel contexts, that is, contextual cueing emerged in both contexts. Slopes in low and high reward contexts did not differ significantly (all $ps \geq .515$).

To investigate whether observers benefited from a local context repetition similarly as from global repetitions, we compared the slopes in local and global contexts. We recalculated the model with global contexts coded as a reference, which revealed that the slope in local contexts was 0.7 ms shallower than in global contexts, $\Delta b = 0.7$ [0.2, 1.3], $t(6962) = 2.57$, $p = .010$. To get a more fine-grained view on this difference, we recalculated the model separately for each session and each reward magnitude. The calculated mixed models were the same as the main model but excluded the effects of reward because each reward magnitude was analyzed separately. Interestingly, the slope was significantly shallower in local than in global contexts only in the second session and in only in low reward contexts, $\Delta b = 0.9$ [0.3, 1.4], $t(1298) = 3.07$, $p = .002$. In all other conditions, there were no significant differences between local and global context slopes (all ps $\geq .385$). The estimated slopes of these separate mixed models are depicted in Figure 2, lower panels.

In sum, the analysis of RTs revealed that participants showed contextual cueing in local and global contexts and that local contexts mostly led to similar benefits in RTs as global contexts did. When considering the impact of reward, no facilitation of the use of local or global contexts was observed, as RT slopes of low and high reward contexts were comparable. However, we observed that the *difference* between local and global contexts depended on the reward magnitude in session 2: While in session 1, participants benefited from local contexts in a similar manner as from global contexts, observers searched local contexts slower than global contexts when color signaled low reward in session 2 (see Figure 2, lower left panel). In high reward contexts, local contexts were searched as fast as global contexts.

Error rates

The mixed model estimated that the error rates decreased 0.6 % with each block in novel contexts, $b = -0.6$ [−0.7, −0.5], $t(101) = -10.98$, $p < .001$. The difference between the slopes in global and novel contexts missed significance, $\Delta b = -0.07$ [−0.15, 0.006], $t(6962) = -1.82$, $p = .069$, and so did the difference between local and novel contexts, $\Delta b = -0.08$ [−0.16, 0.001], $t(6962) = -1.94$, $p = .052$. There were no differences between reward magnitudes (all ps $\geq .522$). When we recalculated the model with global contexts coded as a reference, neither the difference between the slopes in global and local contexts was significant, $\Delta b = -0.005$ [−0.08, 0.07], $t(6962) = -0.12$, $p = .902$. These results indicate that participants made fewer errors when the experiment proceeded, but there were neither differences between context types nor between reward magnitudes.

Fixation count

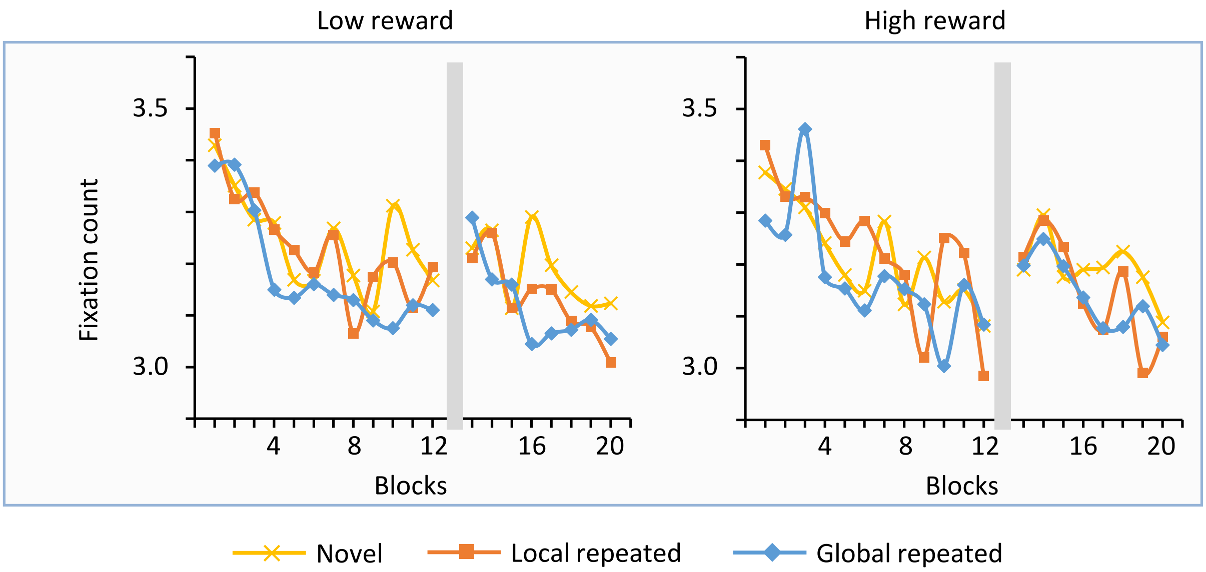

Figure 3. Fixation count during the experiment in low reward (left panel) and high reward contexts (right panel). Fixation count for novel contexts is shown in yellow, for local contexts in orange, and for global in blue. The gray bar stands for the time gap between the sessions.

The fixation count is depicted in Figure 3. Similar to the response times, the mixed model estimated that the average fixation count decreased with each block in novel contexts, $b = -0.008$ [−0.012, −0.004], $t(108) = -3.85$, $p < .001$. Again, the slope in global contexts was estimated steeper than in novel contexts, $\Delta b = -0.006$ [−0.009, −0.003], $t(6937) = -3.64$, $p < .001$. Also the slope in local contexts was steeper than the slope in novel contexts, $\Delta b = -0.004$ [−0.007, −0.0005], $t(6937) = -2.25$, $p = .025$. There were no differences between slopes in low and high reward contexts (all $ps \geq .402$). As for RT, we re-calculated the model with global contexts coded as a reference, which showed that the difference between the slope in global and local contexts was not significant, $\Delta b = 0.002$ [−0.001, 0.005], $t(6937) = 1.39$, $p = .164$. In sum, these results show that participants used both local and global contexts to direct their eyes to the target because they needed fewer fixations compared to novel contexts. This benefit was similar for local and global contexts. Reward affected the fixation count neither in local nor in global contexts.

Differences between gray and colored targets

In the present study, half of the context configuration items were gray and half were colored. Thus, also the target was colored in half of the trials and gray in the other half, and searching for the target in either the subset of gray or colored items was not particularly efficient. However, as color, as a salient feature, predicted reward magnitude, participants might have relied on color to search for the target. If so, this might have particularly affected performance in local contexts, because the local context patch only contained two colored and two gray items (3 distractors and 1 target, cf. Figure 1). Focusing on the colored items would reduce the number of items available for context learning even further, i.e., from four to two, whereas in global contexts still half of the items would be considered. Consequently, focusing on color would have a stronger impact on local contexts, i.e., longer response times for contexts with a gray compared to a colored target.

To examine this consideration, we compared RTs in contexts with gray and colored targets separately for sessions 1 and 2. We collapsed RTs in session 1 (blocks 1-12) and session 2 (blocks 14-20), and calculated a repeated measure ANOVA with the factors *target color* (colored vs. gray), *context type* (novel vs. local vs. global), and *reward* (low vs. high). Block 13 was excluded because participants directly started with this block after the break without additional practice. Results in session 1 showed no differences between contexts with gray and colored targets; the main effect of target color (p = .600) and all interactions including target color missed significance ($ps \geq .270$).

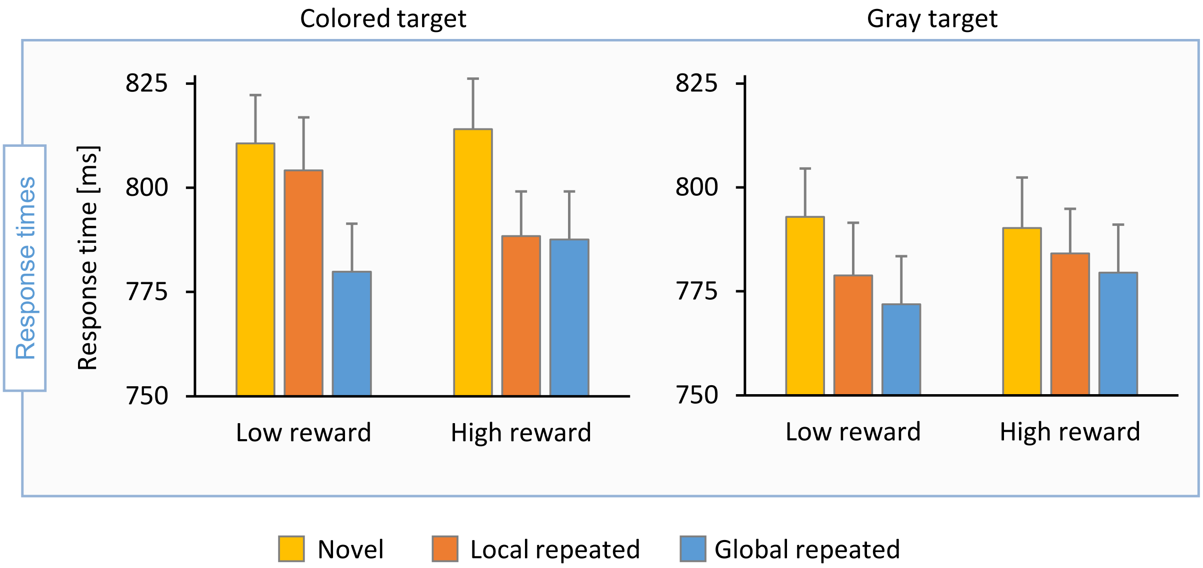

Figure 4. Response times in blocks 14-20, separately for contexts with colored targets (left panel) and gray targets (right panel). Novel contexts are depicted as yellow, local as orange, and global as blue bars. The error bars show the standard error of the mean.

Results in session 2 (see Figure 4) showed a main effect of target color, $F(1, 58) = 7.44$, $p = .008$, $\eta^2_p = .114$, indicating faster RTs in contexts with gray (M = 783 ms, SEM = 11) compared with colored targets (M = 797 ms, SEM = 12), and a significant main effect of context type, $F(2, 116) = 21.18$, $p < .001$, $\eta^2_p = .267$. Pairwise comparisons based on estimated marginal means revealed that RTs in local and global contexts were faster than in novel contexts (ΔM_{local} = 13 ms, *SEM* = 4, p = .001; ΔM_{global} = 22 ms, *SEM* = 4, $p < .001$), and that global contexts were searched faster than local contexts (ΔM = 9 ms, *SEM* = 3, p = .017; p-values are Bonferroni corrected for multiple comparisons). No other effect reached significance (ps $\geq$ .141). In sum, these results show that participants responded *slower* in contexts with colored compared to gray targets in session 2, which would suggest that participants focused on gray items rather than on items in color in that session.

Although not significant, Figure 4 visually suggests a differential effect of reward in local contexts with a colored target (orange bar in left panel of Fig. 4). To examine this possibility, we calculated the mixed model for session 2, separately for low and high reward as visualized in Figure 2, and separately for contexts with gray and colored targets. For low reward contexts with colored targets, the local slope was estimated shallower than the global slope, difference: Δb = 1.4 [0.6, 2.2], $t(1298)$ = 3.49, $p < .001$, while the slopes were similar for high reward contexts (p = .712), and for contexts with gray targets ($p_{low\ reward}$ = .543, $p_{high\ reward}$ = .469). The separate mixed models therefore confirm that in low reward contexts with a colored target, local contexts were searched slower than global contexts in session 2.

General Discussion

The present study examined if observers use local and global context repetitions for finding the target in a similar manner and how reward-predicting context features influence context learning in local and global contexts. Since reward-predicting context features were reported to facilitate attention guidance in global contexts, we speculated that they might also facilitate attention guidance local contexts. We used search contexts in which either the complete context configuration was repeated in each block (global contexts), only a local patch surrounding the target repeated while the remaining context was arranged randomly (local contexts), or in which the complete context was random (novel contexts). Half of the items in the contexts were presented in a color signaling high or low reward magnitude for correct responses. As we assumed, we found contextual cueing (CC) in both local and global contexts, measured as faster response times and fewer fixations compared to novel contexts. In addition, local contexts led to comparable CC effects as global contexts did, which suggests that observers could use local and global context repetitions in a similar manner to detect the target.

Unexpectedly, reward had not much impact on performance, as the slopes observed for high and low reward response times did not differ, neither for local nor for global contexts. We only observed a small effect on local contexts with colored targets in session 2. These results were surprising, since reward has been reported to facilitate task performance in global contexts and we had expected to observe a similar facilitating effect in both local and global contexts.

Local and global context repetitions

Our results showed that local contexts led to comparable CC effects as global contexts: RTs decreased faster in both local and global contexts than in novel contexts, and their slopes did not differ (except for colored targets signaling low reward in session 2, which will be considered at a later point in this discussion). Contextual cueing emerged similarly in both context types (s. Figure 2, lower panels), suggesting that the repetition of only three distractors surrounding the target was sufficient to produce CC effects comparable to repeating all 15 distractors in the display. Fixation count points in the same direction, since the slopes of the fixation count were comparable in local and global contexts, but steeper than in novel contexts. This suggests that attention guidance (as indexed by the fixation count) was comparably efficient in local and global contexts. These results suggest that repetitions of a local context of distractors could be used in a similar manner to detect the target as repetitions of the entire global context configuration.

At first glance, it seems surprising that the repetition of only three distractors led to similar contextual cueing as seen with repeating the entire context configuration. Song and Jiang (2005) reported that, once a context has been learned, the repetition of a minimum of three context items (two distractors and the target) was sufficient to produce a contextual cueing effect. In their study, however, the authors first repeated the entire context configurations in a training phase, which allowed learning to emerge. In a subsequent testing phase, they repeated three items of the previously shown contexts but arranged the remaining items randomly. Testing with these partially repeated contexts was thus separated from learning, done on the entirely repeating context configuration in the separate training phase. In an additional experiment, the authors examined whether three items would also suffice for learning to emerge. Similar to our experiment, the study implied partially repeated contexts with three repeating items, completely repeated contexts, and novel contexts. While participants showed contextual cueing for completely repeated contexts, performance in contexts with three repeating items was as slow as in novel contexts. The authors concluded that the repetition of three items was sufficient for retrieval of an already learned context configuration, but was not enough for learning to evolve.

In contrast to Song and Jiang (2005), we observed contextual cueing also in local contexts with only three distractors repeating during learning. One reason for this difference might be that our local contexts contained three repeated distractors (and the target), whereas Song and Jiang used one object less. A more likely explanation seems that the three distractors of our local contexts were arranged in a spatially defined patch surrounding the target. Novel context items appeared only outside the patch but not within. In Song and Jiang's study, randomly placed distractors also appeared between the three repeating items. These novel items presumably hindered learning an association of the repeating items and the target location (see

Olson & Chun, 2002). Our local contexts might have shown contextual cueing because random items never occupied the space between the three repeated distractors and the target.

Our local contexts however not only showed contextual cueing, but the effect was of similar size as compared to global contexts. One reason for the comparable contextual cueing effects in local and global contexts might be that the display presentation time was limited in our experiment (max. 1000 ms). One might think that participants had not enough time for processing the complete global configuration in this time span, and that they therefore only associated a limited patch with the target also in global contexts. However, it seems more likely that the target patch simply contained sufficient information for guiding attention to the target and that learning the complete global configuration did not provide a significant advantage for the observers. This would also suggest that observers learned a restricted context patch also in global contexts, despite the global context repetition. Brady and Chun (2007) implemented a modelling approach investigating to what extend repeated context configurations are learned in contextual cueing. Their results suggested that, even when the context repeats globally, observers might only learn a local context, which also is responsible for the facilitation of attention guidance to the target. In their results, this local context covered about one *quadrant* of the search display. Since the target patch of our local contexts approximated the quadrant of the target (see Figure 1), it seems very likely that the local contexts provided the observers with sufficient information for context learning to emerge.

In sum, our results suggest that observers use the distractors in the local context of the target to learn to guide attention to the target location. Local contexts presumably were as effective as global contexts, because the target patch was large enough, covering approximately one quadrant of the screen, and because the space between the repeating distractors and the target was never occupied by random novel items.

Proportion of repeated vs novel context trials: The role of predictions in context learning

An aspect of the present study, which might have facilitated learning of local and global context configurations, is the overall proportion of local and global contexts in the experiment. In the present study, each experimental block contained one third global, one third local, and one third novel contexts (cf. Figure 1). Thus, two thirds of trials in the experiment contained contexts in which (at least some) items were repeating, and only one third of trials was entirely novel. This is an important difference to most contextual cueing studies, in which usually only half of the trials in the experiment contain repeating context items (50% global and 50% novel trials, Chun & Jiang, 1998).

The ratio of repeated and novel contexts has a strong impact on the emergence and size of the CC effect (Yang & Merrill, 2015). Zinchenko, Conci, Müller, and Geyer (2018) showed that CC was even absent when contexts repeated in only a small proportion of trials (20 % repeated, 80 % novel). Based on the theory of predictive coding (e.g., de Lange, Heilbron, &

Kok, 2018; Friston, 2005), the authors proposed that learning of repeated contexts can only emerge when observers can generate (implicit) predictions about regularities in the visual environment, and when they are able to evaluate these predictions by processing prediction errors, which are crucial for learning to evolve. Applied to contextual cueing, this would imply that participants use context configurations to generate predictions about potential target locations and, based on the processing of prediction errors, learn to associate repeated context configurations with the embedded target locations.

In the present experiment, participants search through different contexts to find the target, and, after having performed several trials, generate predictions about the likely target location. These predictions can be evaluated by comparing the predicted to the actual target location, and as a consequence, participants can update their predictions for future trials. This mechanism however, requires that the visual environment (here: the contexts) has a consistent and reliable structure that can be perceived by the observer (de Lange et al., 2018; Feldman & Friston, 2010). Although organisms are highly sensitive in registering regularities in space and time (e.g. de Lange et al., 2018; Goujon et al., 2015; Summerfield & de Lange, 2014), an unstructured environment with regularities appearing in only few trials might not allow for reliable predictions. In contextual cueing tasks, regularities can be registered in repeated contexts but not in novel ones, thus the proportion of repeated vs novel contexts seems crucial for learning: The higher the proportion of trials in which (parts of) the context repeat, the higher the frequency of trials in which observers can successfully evaluate their predictions. An adequate amount of repeated context trials ensures that prediction error processing provides the ground for learning. A low proportion on the other hand does mostly not allow for reliable predictions, which hinders learning.

The results of Zinchenko et al. (2018) support this consideration, because they showed contextual cueing with a high proportion of repeated contexts, but not with a low proportion. The higher number of repeated contexts seemed to have constituted an environment that allowed for an efficient processing of prediction errors and, accordingly, favored the emergence of context configuration learning. A low proportion of repeated contexts, however, was suggestive of an unstructured environment and hindered context learning. In our experiment, (parts of) the context configuration repeated in two thirds of the trials, either locally around the target location, or as global context configuration. Participants seemed to have perceived this combination of local and global repeated contexts as reliable environment and the amount of both context types seemed to have provided prediction error signals adequate for learning. Presumably, the fact that participants received feedback about their task performance in each trial might have further contributed to the perceived reliability and the observed context configuration learning.

Lack of reward effects in the present study

Although participants showed robust contextual cueing, reward magnitude seemed to have played no role for context learning. In other words, expecting a high reward did not speed responses in any of the contexts when compared to expecting a low reward. This was an unexpected finding that stands in contrast to prior findings reporting faster responses with high reward in global contexts (e.g., Bergmann, Koch et al., 2019; Pollmann et al., 2016). Accordingly, we had assumed that expecting a high (compared to low) reward would increase contextual cueing by facilitating attention guidance in local and in global contexts, and by strengthening the association of the repeated context configuration and the target location in learning (Bergmann, Koch et al., 2019; Tseng & Lleras, 2013). This would have been beneficial for task performance in global and in local contexts, since attention could be guided more efficiently to the target when the contexts reappeared.

The results, however, seem to suggest that participants did not learn to expect a high or a low reward based on the color in the display. When asked for having noticed any regularities during the experiment in the post-experimental questionnaire, only about one quarter of the participants (15 of 59) reported the correct color-reward association. This suggests that the color-reward association was rather subtle and not easily recognized. Several studies have shown that participants need not be aware of the reward scheme for reward to become effective in attention guidance (Failing & Theeuwes, 2018; Feldmann-Wüstefeld et al., 2016). However, it seems striking that the color-reward association went unnoticed by so many participants, although the color-reward magnitude association was consistent, and reward feedback was provided after each response and in each trial. Although immediate feedback usually facilitates learning, most of our participants missed to associate color with reward magnitude.

It seems puzzling that the task allowed for efficient context learning even in contexts with only three repeating distractors but, at the same time, participants did not learn to expect reward based on the color. As outlined in the previous section, the large proportion of local and global contexts in the experiment (2/3 of trials) presumably facilitated context learning. However, there was not only a large proportion, but also a large absolute number of individual local and global contexts in a block. One block contained 16 local and 16 global contexts, considerably more than in previous studies (Bergmann, Koch et al., 2019 used 24 repeated contexts; other studies used only 12). Learning that many different configurations required a lot of learning resources and, when assuming that resources are limited, learning the color-reward association might have received less priority and fewer resources, or there might have been no resources left. In line with this idea, there is evidence that resources for context configuration learning are limited, at least within one experimental session (Schlagbauer, Müller, Zehetleitner, & Geyer, 2012; Smyth & Shanks, 2008).

When participants perform several contextual cueing sessions separated by sleep, they have been reported to be able to learn a large amount of context configurations (Jiang, Song,

& Rigas, 2005, see also Geyer, Müller, Assumpcao, & Gais, 2013). These findings indicate that learning resources become available after contextual cueing has evolved and context learning has been consolidated. Thus, participants might have no resources left for learning at the end of a long contextual cueing session, but might regain them when starting a second contextual cueing session on the next day.

Although highly speculative, regained resources might explain why we observed differential results in session 2, but not in session 1.Since performance improved equally well with local and global contexts in session 1 (as indexed by the similar slopes), participants might have used the regained resources for focusing on other aspects of the experiment in session 2. For instance, they might have tried to figure out the role of the colored items in the experiment, or a potential relation of color and reward magnitude. This would explain the counterintuitive finding that participants became slower in responding to colored targets (which could be green or orange) than to gray targets in that session. In addition, this might also explain the surprising result that local contexts with colored targets were searched slower than global contexts in session 2, since the local target patch contained only few items, making a focus on color more likely and also more distracting than in global contexts. However, these considerations are speculative at this point and it remains open how exactly participants used color in session 2 of the present study.

Conclusion

The present study shows that repeating few items in contextual cueing leads to contextual cueing effects of comparable size as seen when repeating the entire context configuration. This result suggest that observers can use a local target patch to detect the target in a similar manner as the entire context configuration. Our results further suggest that participants use multiple information to search for targets when they have available resources allowing for such a behavior. This finding fits to recent results demonstrating that participants integrate irrelevant features into their search behavior when they can be registered without attentional resources (Bergmann, Tünnermann, & Schubö, 2019).

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References

Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39. https://doi.org/10.1111/nyas.12957

Annac, E., Conci, M., Müller, H. J., & Geyer, T. (2017). Local item density modulates adaptation of learned contextual cues. *Visual Cognition*, *25*(1-3), 262–277. https://doi.org/10.1080/13506285.2017.1339158

Beesley, T., Hanafi, G., Vadillo, M. A., Shanks, D. R., & Livesey, E. J. (2018). Overt attention in contextual cuing of visual search is driven by the attentional set, but not by the predictiveness of distractors. *Journal of experimental psychology. Learning, memory, and cognition*, *44*(5), 707–721. https://doi.org/10.1037/xlm0000467

Beesley, T., Vadillo, M. A., Pearson, D., & Shanks, D. R. (2015). Pre-exposure of repeated search configurations facilitates subsequent contextual cuing of visual search. *Journal of experimental psychology. Learning, memory, and cognition*, *41*(2), 348–362. https://doi.org/10.1037/xlm0000033

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of vision*, *19*(3), 1–18. https://doi.org/10.1167/19.3.10

Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on?: Adapting to color while searching for shape. *Attention, perception & psychophysics*, *16*(3). https://doi.org/10.3758/s13414-019-01858-6

Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision research*, *171*, 53–63. https://doi.org/10.1016/j.visres.2020.03.010

Brady, T. F., & Chun, M. M. (2007). Spatial constraints on learning in visual search: modeling contextual cuing. *Journal of experimental psychology. Human perception and performance*, *33*(4), 798–815. https://doi.org/10.1037/0096-1523.33.4.798

Chelazzi, L., Perlato, A., Santandrea, E., & Della Libera, C. (2013). Rewards teach visual selective attention. *Vision research*, *85*, 58–72. https://doi.org/10.1016/j.visres.2012.12.005

Chun, M. M. (2000). Contextual cueing of visual attention. *Trends in Cognitive Sciences*, *4*(5), 170–178. https://doi.org/10.1016/S1364-6613(00)01476-5

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: implicit learning and memory of visual context guides spatial attention. *Cognitive psychology*, *36*(1), 28–71. https://doi.org/10.1006/cogp.1998.0681

de Lange, F. P., Heilbron, M., & Kok, P. (2018). How Do Expectations Shape Perception? *Trends in Cognitive Sciences*, *22*(9), 764–779. https://doi.org/10.1016/j.tics.2018.06.002

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. https://doi.org/10.1037/0033-295X.96.3.433

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

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

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

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; a journal devoted to the study of the nervous system and behavior*, *102*, 67–95. https://doi.org/10.1016/j.cortex.2017.09.027

Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1456), 815–836. https://doi.org/10.1098/rstb.2005.1622

Geyer, T., Müller, H. J., Assumpcao, L., & Gais, S. (2013). Sleep-effects on implicit and explicit memory in repeated visual search. *PloS ONE*, *8*(8), e69953. https://doi.org/10.1371/journal.pone.0069953

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Harris, A. M., & Remington, R. W. (2017). Contextual cueing improves attentional guidance, even when guidance is supposedly optimal. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(5), 926–940. https://doi.org/10.1037/xhp0000394

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

Jiang, Y., & Chun, M. M. (2001). Selective attention modulates implicit learning. *The Quarterly Journal of Experimental Psychology A*, *54*(4), 1105–1124. https://doi.org/10.1080/02724980042000516

Jiang, Y., & Leung, A. W. (2005). Implicit learning of ignored visual context. *Psychonomic bulletin & review*, *12*(1), 100–106. https://doi.org/10.3758/BF03196353

Jiang, Y., & Song, J.-H. (2005). Hyperspecificity in visual implicit learning: Learning of spatial layout is contingent on item identity. *Journal of experimental psychology. Human perception and performance*, *31*(6), 1439–1448. https://doi.org/10.1037/0096-1523.31.6.1439

Jiang, Y., Song, J.-H., & Rigas, A. (2005). High-capacity spatial contextual memory. *Psychonomic bulletin & review*, *12*(3), 524–529. https://doi.org/10.3758/BF03193799

Kunar, M. A., Flusberg, S. J., & Wolfe, J. M. (2006). Contextual cuing by global features. *Perception & Psychophysics*, *68*(7), 1204–1216. https://doi.org/10.3758/BF03193721

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (2015). When goals conflict with values: counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of experimental psychology: General*, *144*(1), 158–171. https://doi.org/10.1037/xge0000037

Li, A.-S., & Theeuwes, J. (2020). Statistical regularities across trials bias attentional selection. *Journal of Experimental Psychology: Human Perception and Performance.* Advance online publication. https://doi.org/10.1037/xhp0000753

Olson, I. R., & Chun, M. M. (2002). Perceptual constraints on implicit learning of spatial context. *Visual Cognition*, *9*(3), 273–302. https://doi.org/10.1080/13506280042000162

Peterson, M. S., & Kramer, A. F. (2001). Attentional guidance of the eyes by contextual information and abrupt onsets. *Perception & Psychophysics*, *63*(7), 1239–1249. https://doi.org/10.3758/BF03194537

Pollmann, S., Eštočinová, J., Sommer, S., Chelazzi, L., & Zinke, W. (2016). Neural structures involved in visual search guidance by reward-enhanced contextual cueing of the target location. *NeuroImage*, *124*(Pt A), 887–897. https://doi.org/10.1016/j.neuroimage.2015.09.040

Schlagbauer, B., Geyer, T., Müller, H. J., & Zehetleitner, M. (2014). Rewarding distractor context versus rewarding target location: a commentary on Tseng and Lleras (2013).

Attention, perception & psychophysics, *76*(3), 669–674. https://doi.org/10.3758/s13414-014-0668-5

Schlagbauer, B., Müller, H. J., Zehetleitner, M., & Geyer, T. (2012). Awareness in contextual cueing of visual search as measured with concurrent access- and phenomenal-consciousness tasks. *Journal of vision*, *12*(11), 1–12. https://doi.org/10.1167/12.11.25

Sharifian, F., Contier, O., Preuschhof, C., & Pollmann, S. (2017). Reward modulation of contextual cueing: Repeated context overshadows repeated target location. *Attention, perception & psychophysics*. (79), 1871–1877. https://doi.org/10.3758/s13414-017-1397-3

Smyth, A. C., & Shanks, D. R. (2008). Awareness in contextual cuing with extended and concurrent explicit tests. *Memory & Cognition*, *36*(2), 403–415. https://doi.org/10.3758/MC.36.2.403

Song, J.-H., & Jiang, Y. (2005). Connecting the past with the present: How do humans match an incoming visual display with visual memory? *Journal of vision*, *5*(4), 322–330. https://doi.org/10.1167/5.4.4

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

Thaler, L., Schütz, A. C., Goodale, M. A., & Gegenfurtner, K. R. (2013). What is the best fixation target? The effect of target shape on stability of fixational eye movements. *Vision research*, *76*, 31–42. https://doi.org/10.1016/j.visres.2012.10.012

Theeuwes, J. (2018). Visual Selection: Usually Fast and Automatic; Seldom Slow and Volitional. *Journal of Cognition*, *1*(1), 67. https://doi.org/10.5334/joc.13

Tseng, Y.-C., & Li, C.-S. R. (2004). Oculomotor correlates of context-guided learning in visual search. *Perception & Psychophysics*, *66*(8), 1363–1378. https://doi.org/10.3758/BF03195004

Tseng, Y.-C., & Lleras, A. (2013). Rewarding context accelerates implicit guidance in visual search. *Attention, perception & psychophysics*, *75*(2), 287–298. https://doi.org/10.3758/s13414-012-0400-2

Võ, M. L.-H., & Wolfe, J. M. (2012). When does repeated search in scenes involve memory? Looking at versus looking for objects in scenes. *Journal of experimental psychology. Human perception and performance*, *38*(1), 23–41. https://doi.org/10.1037/a0024147

Wang, B., & Theeuwes, J. (2020). Implicit attentional biases in a changing environment. *Acta Psychologica*, *206*, 103064. https://doi.org/10.1016/j.actpsy.2020.103064

Yang, Y., & Merrill, E. C. (2015). The impact of signal-to-noise ratio on contextual cueing in children and adults. *Journal of experimental child psychology*, *132*, 65–83. https://doi.org/10.1016/j.jecp.2014.12.005

Zang, X., Jia, L., Müller, H. J., & Shi, Z. (2015). Invariant spatial context is learned but not retrieved in gaze-contingent tunnel-view search. *Journal of experimental psychology. Learning, memory, and cognition*, *41*(3), 807–819. https://doi.org/10.1037/xlm0000060

Zellin, M., Mühlenen, A. von, Müller, H. J., & Conci, M. (2014). Long-term adaptation to change in implicit contextual learning. *Psychonomic bulletin & review*, *21*(4), 1073–1079. https://doi.org/10.3758/s13423-013-0568-z

Zhao, G., Liu, Q., Jiao, J., Zhou, P., Li, H., & Sun, H.-j. (2012). Dual-state modulation of the contextual cueing effect: Evidence from eye movement recordings. *Journal of vision*, *12*(6), 1–13. https://doi.org/10.1167/12.6.11

Zinchenko, A., Conci, M., Müller, H. J., & Geyer, T. (2018). Predictive visual search: Role of environmental regularities in the learning of context cues. *Attention, perception & psychophysics*, *80*(5), 1096–1109. https://doi.org/10.3758/s13414-018-1500-4

Study IV

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https://doi.org/10.3758/s13414-019-01858-6

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Which search are you on? Adapting to color while searching for shape

Nils Bergmann[1] • Jan Tünnermann[1] • Anna Schubö[1]

Abstract
Human observers adjust their attentional control settings when searching for a target in the presence of predictable changes in the target-defining feature dimension. We investigated whether observers also adapt to changes in a nondefining target dimension. According to feature integration theory, stimuli that are unique in their environment in a single feature dimension can be detected with little effort. In two experiments, we studied how observers searching for such singletons adapt their attentional control settings to a dynamical change in a nondefining target dimension. Participants searched for a shape singleton and freely chose between two targets in each trial. The two targets differed in color, and the ratio of distractors colored like each target varied dynamically across trials. A model-based analysis with a Bayesian estimation approach showed that participants adapted their target choices to the color ratio: They tended to select the target from the smaller color subset, and switched their preference both when the color ratio changed between gray and heterogeneous colors (Exp. 1) and when it changed between red and blue (Exp. 2). Participants thus tuned their attentional control settings toward color, although the target was defined by shape. We concluded that observers spontaneously adapted their behavior to changing regularities in the environment. Because adaptation was more pronounced when color homogeneity allowed for element grouping, we suggest that observers adapt to regularities that can be registered without attentional resources. They do so even if the changes are not relevant for accomplishing the task—a process presumably based on statistical learning.

Keywords Selective attention · Feature integration · Visual search · Attentional control · Adaptive choice visual search

Humans have to find their way in a visually complex and dynamic world, filled with stimuli ranging from simple features to complex objects, which can be at rest or in motion and inanimate or socially relevant. "Selective visual attention" refers to those mechanisms that enable us to adapt to this complex environment with great ease in many situations.

Anne Treisman's feature integration theory (e.g., Treisman & Gelade, 1980) suggested a two-stage model in which a phase of preattentive, parallel processing is followed by a sequential attentional stage. Basic features, such as color or shape, can be processed preattentively, whereas more complex feature conjunctions require "binding," which is performed by focusing attention. Visual search tasks in which observers have to find a target that differs in a single, salient feature from surrounding distractors showed that observers are highly efficient in doing so, irrespective of the number of distractors. For targets defined via conjunctions of features, the search is substantially less efficient, and the time until the target is found increases with the number of distractors, indicating that observers iterate serially through the elements.

To what degree the processing of salient items ("singletons") is stimulus-driven and automatic, or whether search is contingent on goal-directed attentional control settings, has been a subject of intense debate over the last decades (e.g., Folk & Remington, 1998; Folk, Remington, & Johnston, 1992; Gaspelin, Ruthruff, & Lien, 2016; Kim & Cave, 1999; Theeuwes, Olivers, & Belopolsky, 2010; see also Awh, Belopolsky, & Theeuwes, 2012; Gaspelin & Luck, 2018; Theeuwes, 2018). Observers use knowledge about target-defining features to adjust their attentional control setting and to focus on specific subsets of items—for instance, on all items of a specific color. This allows them to restrict search to a subset of relevant features (Egeth, Virzi, & Garbart, 1984; Sobel & Cave, 2002; Sun, Chubb, Wright, & Sperling, 2016) and to avoid attending to irrelevant ones, which in turn increases search efficiency. However, despite the ability to direct visual search with attentional control settings, observers do

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not always apply them (Bacon & Egeth, 1994; Kadel, Feldmann-Wüstefeld, & Schubö, 2017).

The selection of appropriate attentional control settings is especially important in complex and unconstrained environments, where observers typically do not know which stimuli are relevant and worth attending (Gottlieb, 2012; Gottlieb, Hayhoe, Hikosaka, & Rangel, 2014). Under such conditions, human observers have to evaluate whether the current setting is efficient in the task at hand or whether they have to adjust them (e.g., Botvinick & Braver, 2015; Braver, 2012). A new branch of visual attention research therefore includes choice as a measure of attentional control (e.g., Irons & Leber, 2016; Kristjánsson, Jóhannesson, & Thornton, 2014; Wolfe, 2013; Wolfe, Cain, & Aizenman, 2019).

Choice as a measure of attentional control was examined by Irons and Leber (2016) with the adaptive choice visual search task. Their search displays consisted of differently colored squares that were either small or large. Participants had to choose one of two targets that were small, and either blue or red. Across trials, some of the distractors gradually changed their color from red to blue and back. Since participants were informed about the changing distractors, and they were free to pick whichever target they preferred in each trial, the authors assumed that the changing distractor color influences target choice. They suggested that participants counteracted the gradual color change in the distractors by selecting the target that was less similar to the majority of distractors in the display.

Irons and Leber's (2016) results showed that some observers adapted their target choice to the color change across the trial sequence: They preferred the red target when it was presented among increasingly blue distractors, and they switched to blue when the distractors changed toward red. However, a substantial number of individuals barely adapted, presumably because adaptation was effortful and participants were attempting to minimize their effort. Irons and Leber (2016) concluded that attentional control is governed by tendencies toward both performance maximization and effort minimization (see also Irons & Leber, 2018). Overall, these results highlight that observers learn target-related regularities in dynamically changing environments and adjust their attentional control accordingly.

In a variation of the adaptive choice visual search task, we explored how observers would adapt their selection behavior if they did not know about the dynamically changing trial sequence and if—in contrast to Irons and Leber (2016, 2018)—color was no longer required for finding one of the targets. Participants had to select one of two shape singleton targets that were presented among distractors of a different shape. The color ratio of all display items changed dynamically across trials. A trial sequence started with one uniquely colored item (which was always one of the targets), and the number of items in similar colors increased by one from trial to trial.

Because color is a feature that enables preattentive processing (Treisman, 1988) and that can capture attention even when it is task-irrelevant (Theeuwes, 2004, 2010, 2013, 2018), we hypothesized that participants would be affected by the dynamically changing ratio of distractor colors: We assumed that participants started by selecting the uniquely colored target and continued adjusting their target choices with respect to the changing color ratio in the displays.

The adaptive choice visual search task is a relatively new and particularly unconstrained task, thus our study inherently has an exploratory component. Participants' selection behavior might not be affected by the changing color ratio at all. Alternatively, participants might adjust their attentional control settings in a similar way as observed in Irons and Leber (2016) study. If so, this would indicate that target choice adaptation is not limited to changes in target-defining feature dimensions.

Rationale of the present study

In two experiments we investigated whether a change in the appearance of distractors affects target choice, even if the change occurs in a dimension that must not necessarily be considered to detect a target. In particular, participants reported one of two shape singleton targets presented among circle distractors. This difference in shape clearly distinguished targets from distractors, and the task could be accomplished without taking any further properties of the items into account. However, the two targets could also be in one of two color states, which was always different between the targets. A variable proportion of distractors shared the color state with either target. In Experiment 1 the color states were "colored" (colored items had different hues of blue) and "noncolored" (gray). In Experiment 2, the color states were blue or red. Over the course of an experimental block, the proportion of distractors in each color state changed systematically.

As is depicted in Fig. 1, for Experiment 1, blocks started in plateaus (three trials: P1, P2, and P3) in which all distractors had the same color state and only one of the targets was in the other state. In this example, all distractors were noncolored ("gray plateau"); only one of the diamond targets was colored. In subsequent trials, the proportion of colored distractors increased one by one until all distractors were in the colored state ("color plateau"). In this plateau, one of the targets was the only gray item in the display. A reverse transition then led back to a gray plateau.

This type of task can be accomplished by searching for a shape singleton (the diamond) and ignoring color, since color is not required in order to find a target. However, since the two targets differ in their color state, participants can also make use

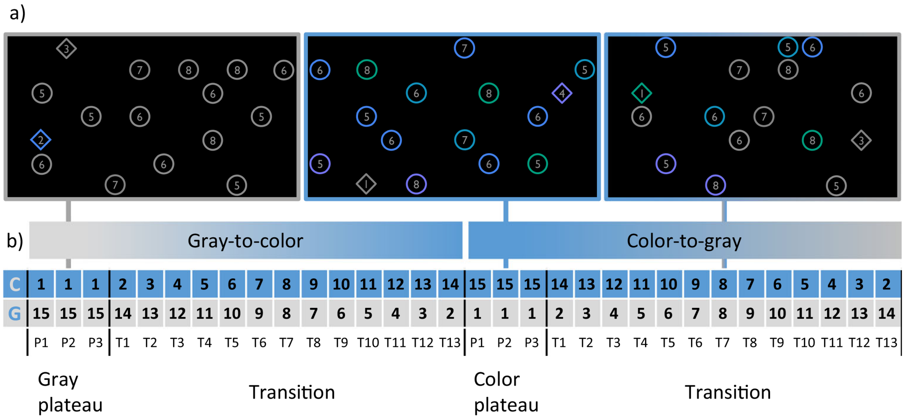

Fig. 1 Exemplary search displays and trial sequence in a block of Experiment 1. The search display always contained two shape targets (diamonds) and fourteen distractors (circles). One target was always gray and the other colored. The proportions of gray and colored distractors transitioned from gray plateaus (no color distractors: A, left display) to color plateaus (no gray distractors: A, middle display). Panel B shows the numbers of gray ("G") and colored ("C") items in the display in each trial.

of the dynamical change in distractor colors to select their target. They might prefer targets whose color state is rare in the display because (1) fewer items stand out from the background and (2) fewer items have to be inspected to find the target. In the plateaus, both aspects come together and provide their maximum utility in facilitating search, since there is only a single salient item: one of the diamond-shaped targets. Most theories of attentional selection would assume that participants prefer to select such a target. However, from the first plateau toward the center of the transition, selecting this target becomes less efficient, because the proportion of distractors in the same color state as the target increases. If participants adapt their target choice to the color ratio, they are likely to switch to the target with the other color state near the center of the transition, as the proportion of distractors in this color state decreases. This adaptation requires participants to estimate the proportion of items in one or the other color state, and it is likely that observers will not perform this estimation with absolute accuracy. It is also likely that observers will not show target choice adaptation in every trial, since Irons and Leber (2016) observed a considerable amount of apparently spontaneous target switches. We therefore modeled the tendency to adapt to the color change during the transition with a psychometric function (see, e.g., Woodworth & Schlossberg, 1954), as depicted in Fig. 2. For every trial in the transition, the function returns the probability of selecting that target whose color state was unique in the starting plateau. The tendency to adapt target choice (adaptive choice [AC] tendency) is reflected in the slope of the curve. The figure depicts exemplary slopes, including extreme cases of no adaptation (flat line) and the ideal observer (step function that instantly falls from 1 to 0). The trial in the transition at which participants are likely to select either of the two targets with the same probability is the point of subjective equality (PSE), because whichever influences bias the choice at other transition trials are subjectively equal and balance target choice at this trial. In our evaluation, we fitted a formal version of this model to the experimental data in a Bayesian estimation procedure at the participant level. The estimates of AC tendency and PSE allowed a differentiated analysis of how individuals perform the task that goes beyond the discussion of average curves of target choices used in similar studies.

Experiment 1

Method

Participants

Forty volunteers (31 female, nine male), naive to the paradigm and objective, participated for course credit or payment. The participants were between 19 and 30 years old ($M = 22.4$, $SD = 3.21$), had normal or corrected-to-normal visual acuity and normal color vision (both tested with Oculus Binoptometer 3). Participants attested written understanding and consent before the experiment started. The experiment was conducted in accordance with the ethical standards of the Declaration of Helsinki and was approved by the Ethics Committee of the Faculty of Psychology at Philipps-University Marburg.

Apparatus

Participants sat in a comfortable chair in a dimly lit and sound attenuated room. They used their index and middle fingers of both hands to press one of four buttons at the backside of a gamepad (Speedlink STRIKE Gamepad). The stimuli were presented on a LCD-IPS screen (Cambridge Research

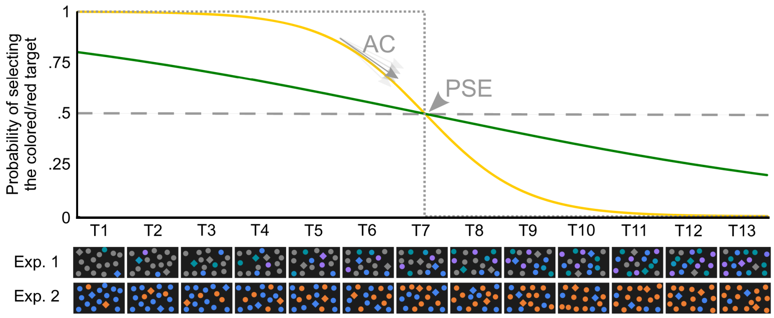

Fig. 2 Visualization of adaptive target choice. The dotted gray line represents an "ideal observer" who always selects the target in the color state that is less frequent at the *starting* plateau. Less ideal, more realistic observers will adapt only to some extent, as is shown by the shallower slope (lower AC) of the solid yellow line. Weak adaptation produces curves such as the green one. Random selection of the target produces flat lines (dashed gray line). The point of subjective equality (PSE) describes the trial in which observers switch their preference from one target to the other. The cartoon displays at the bottom illustrate the changing distractor color states in Experiments 1 and 2.

Systems, Display++ LCD Monitor 32 in., 1,920 × 1,080 pixels, 120 Hz), placed 100 cm in front of participants. A Windows 7 PC running E-Prime Professional (2.0.10.356) controlled stimulus presentation and response collection.

Stimuli and general procedure

The search displays always consisted of 16 items—14 circles (distractors) and two diamonds (targets)—sparsely distributed on an imaginary 12 × 7 grid (see Fig. 1A). All items had a diameter of 1.66° and were presented with a minimal distance of 1.66° between any two items. The two diamond targets could appear in eight target locations, four on each side of the screen, arranged semicircularly on both sides with an average distance of 14.52° (*SD* = 0.47) from screen center. The two target positions were selected randomly among these locations in each trial. Fourteen distractors were placed randomly on the grid. The stimuli were gray (RGB 122, 122, 122; 55.85 cd/m^2) or colored on a black background (RGB 0, 0, 0; 0.16 cd/m^2); color was chosen randomly for each item in each trial from a set of four colors: turquois (RGB 0, 170, 136; 55.86 cd/m^2), light blue (RGB 18, 152, 197; 55.80 cd/m^2), dark blue (RGB 64, 131, 237; 55.86 cd/m^2), or purple (RGB 111, 111, 240; 55.84 cd/m^2). A gray digit (Gill Sans MT, font height 0.46°) was placed in the center of each item. The targets contained different random digits between 1 and 4; distractors contained random digits from 5 to 8.

In each trial, the search display included one gray and one colored diamond target along with 14 circle distractors. The proportions of colored and gray distractors varied systematically across consecutive trials, from "gray plateaus" in which all distractors were presented in gray, to "color plateaus" in which all distractors were colored (cf. Fig. 1). In the gray plateaus (three successive trials), the colored target was the only colored item in the search display, whereas in color plateaus (also three successive trials), the gray target was the only gray item in the display. The plateau was followed by a transition phase of 13 trials in which the proportion of colored distractors successively increased by one (transition from gray plateau to color plateau) or decreased by one (transition from color plateau to gray plateau) in every trial. An experimental block consisted of 32 trials, starting with a plateau (three trials), followed by a transition phase (13 trials), the opposite plateau (three trials), and a transition phase back to the first plateau (13 trials; see Fig. 1B). The starting plateau was balanced across the participants.

Experimental procedure

The experiment consisted of two experimental sessions on separate days with one day in between. The first session started with two practice blocks of the free-choice visual search task (16 trials each), in which the participants were free to select either target. These practice blocks consisted of balanced displays containing a constant proportion of eight colored and eight gray items. After the practice, participants worked through 21 blocks of the free-choice task. The session ended with the Corsi block and the color Stroop task of the PEBL Test Battery. Participants then filled the follow-up survey, in which they were asked to report their strategy for selecting the target and to report any regularities they might have noticed. The second session started with the forced-choice task, which was followed by the informed-choice task. Although the instructions differed across the free-choice, informed-choice, and forced-choice task, the search display and general procedure was the same in all three tasks.

Free-choice task The *free-choice task* was conducted to evaluate which target was chosen in each trial. Participants were informed that the search displays always contained two shape targets (diamonds among circles) and that they were free to choose either one. They were asked to identify the digit presented inside the chosen target and to respond by pressing the corresponding button on the gamepad (1, 2, 3, or 4).

Participants were neither informed about the trial sequence, nor that one target was always colored and one always gray, nor were they given particular instructions about how to choose between the targets.

Trials started with a central fixation dot surrounded by a thin line. After 1,000 ms the thin line disappeared, and after 500 ms the search display was shown. It was presented until participants reported the chosen target, and then it was replaced by an empty black screen presented for 800 ms. After each block, performance feedback (mean response time and accuracy) was presented, followed by a pause of at least 5 s. Participants performed 672 trials of the free-choice task (21 blocks with 32 trials).

Informed-choice task In the *informed-choice task*, participants were informed about the dynamically changing trial sequence and about the number of trials in the plateau and transition phase. Participants were encouraged to adapt their target choice to the changing color ratio, but they were also told that they were still free to select any target in each trial. Participants performed 224 trials (seven blocks with 32 trials) of the informed-choice task.

Forced-choice task In the *forced-choice task*, participants searched for a specific target (either the gray or the colored target) throughout an entire block. This task allowed us to assess response times (RTs) for each target in the trial sequence. A textual cue indicated the relevant target at the beginning of each block. Participants performed 448 trials, split into seven blocks (with 32 trials) in each search condition.

Individual differences: Covariates In addition to the three variations of the visual search task, we assessed the individual working memory capacity and the capability of attentional filtering, which are known to be associated with attentional control (e.g., Fukuda & Vogel, 2011; Fukuda, Woodman, & Vogel, 2015; Jost, Bryck, Vogel, & Mayr, 2011; Robison & Unsworth, 2017).

Participants performed a computerized version of the Corsi block-tapping task, to assess individual visuospatial short-term memory capacity (Corsi block span), and the color Stroop task, as a measure for the capacity to inhibit irrelevant information (RT increase in incongruent relative to congruent trials). Both tasks were taken from the PEBL Test Battery (PEBL Portable 0.14; Mueller & Piper, 2014).

Data analysis

Throughout the analyses, we used Bayesian estimation (Kruschke & Liddell, 2018) and made inferences based on parameter differences. When explicit models were applied, we report the posteriors of the parameters and differences of interest. The ranges of the 95% highest probability density (HPD) intervals are reported in square brackets after the estimates. If the 95% HPD interval of a difference does not include zero, a null effect is highly improbable.

When percentages of target choices were assessed (e.g., in the plateaus or the overall transitions), the success probabilities of binomial distributions over the trial repetitions were estimated. They are reported as percentages or differences in percentage points with their 95% HPD intervals. For comparisons of RTs, the BEST procedure (a Bayesian version of a two-sample t test, see Kruschke, 2013) was applied, and means, differences, and the 95% HPDs are reported. For investigating potential correlations, a Bayesian estimation of Pearson's coefficient (see Ly, Verhagen, & Wagenmakers, 2016; tests were executed in JASP [JASP Team, 2018]) was conducted (and r is reported with its 95% HPDs). If not indicated otherwise, the two-sided test was used.

Target choices Target choices were assessed in the free-choice task and compared to the choices in the informed-choice task, separately for the gray-to-color and color-to-gray transition. Trials with button presses not corresponding to a digit presented inside one of the targets were removed (2.6% in free choice, 2.8% in informed choice). To quantitatively analyze the target choices, a graphical Bayesian model was implemented, which estimates the adaptive choice (AC) tendency and PSE with an S-shaped psychometric function as visualized in Fig. 2. This function describes the probability of selecting the target whose color state was unique in the plateau and became more frequent during a transition. It can be formalized with a sigmoid based on a cumulative Gaussian distribution (cf. Wichmann & Hill, 2001):

$$\Psi(t, AC, PSE) = \frac{1}{2}\operatorname{erf}\left(-\frac{\sqrt{AC} * (t - PSE)}{\sqrt{2}}\right) + \frac{1}{2}, \qquad (1)$$

where t is the trial in the transition, erf is the Gaussian error function, PSE is the trial at which the function crosses the .5 level, and AC the slope of the function (cf. Fig. 2), and an index of how strongly participants adapt. Formally, AC is the precision (inverse of the variance) of the underlying Gaussian distribution. The PSE is the point of subjective equality—that is, the trial in the transition at which observers select each target at the chance level of .5.

This function is at the core of the graphical Bayesian model we used to estimate the participant and mean parameters (see Fig. 3). At the inner levels, a binomial distribution models the number of trials (y_{jt}) (out of all repetitions n_{jt} of that transition trial t) in which participant j selects a target of a particular type (i.e., the colored or gray one). The success probability θ_{jt} is calculated via the psychometric function $\Psi(t, AC_j, PSE_j)$ (Eq. 1) for each trial in the transition. The overall distributions of AC_μ and PSE_μ are sampled as means of the individual

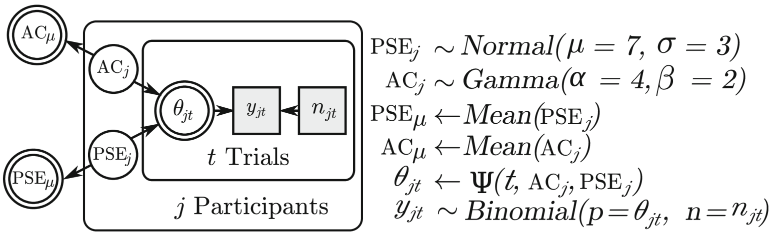

Fig. 3 Graphical model that connects the parameters of interest to binomial likelihoods at every level. The distributions and deterministic relations at every node and the priors are listed to the right.

estimates. The priors used in the evaluation are stated in Fig. 3. They have been selected to be weakly informative: The PSE priors are broad normal distributions centered at the objective point of equality (T7). Gamma distributions on the AC parameters assign most of the density to values in the range from 0 to 5, which corresponds to the spectrum from entirely flat adaptation curves to immensely steep ones that drop from 1 to 0 from one trial to the next (cf. Fig. 2).

The estimation procedure was implemented in PyMC3 (Salvatier, Wiecki, & Fonnesbeck, 2016) and 20,000 samples were drawn using NUTS (Hoffman & Gelman, 2014) after the same number of tuning iterations. For our experiments, we report the AC and PSE means over participants and assess relationships between estimates for different transitions on the participant level.

Response times The RTs in the forced-choice task, in which participants had to select a specific target during one block, were analyzed as an index of the efficiency of finding either target. The mean RTs were assessed for each trial in the plateaus (P1–P3) and transitions (T1–T13) and were aggregated separately for trials in which participants selected the gray or the colored target. With the number of distractors sharing the target's color state increasing or decreasing during the transition, this task is somewhat similar to a standard visual search task in which the set size increases or decreases. Therefore, the usual data pattern with RTs depending on the set size was expected. To analyze search efficiency in the forced-choice task, we estimated search slopes by fitting the following linear function to the mean RTs at the transitions trials t:

$$\mathrm{RT}(t) = \mathrm{RT}_{\mathrm{T7}} + (t - 7) \cdot slope. \tag{2}$$

Subtracting the value 7 from the trial position in the transition centers the function at T7, so that $\mathrm{RT}_{\mathrm{T7}}$ is an estimate of the RT at the center of the transition, where both color states were equally frequent. The slope parameter reflects the increase (or decrease, for negative values) in difficulty in milliseconds per item.

We fitted this function with a Bayesian graphical model, similar to the one depicted in Fig. 3, so that $\mathrm{RT}_{\mathrm{T7}j}$ and slope$_j$ were estimated at the participant level and fed into the overall estimates $\mathrm{RT}_{\mathrm{T7}\mu}$ and slope$_\mu$. The priors were set up as follows: $\mathrm{RT}_{\mathrm{T7}_j}, Normal(\mu = 1{,}000, SD = 300)$; slope$_j$, Normal ($\mu = 0$, $SD = 40$); common standard deviation of all RT(t), $SD_{\mathrm{RT}_j}, Normal(\mu = 0, SD = 500)$.

Results

Target choices

Free-choice and informed-choice tasks Overall, the target choice results revealed that participants adapted their choice to the trial sequence in free choice task (Fig. 4). However, adaptive choice behavior was more pronounced in the informed-choice task than in the free-choice task.

In the plateaus in the free-choice task (Fig. 4, upper panels), participants showed a tendency to select the target in a unique color state. These targets were selected with a probability of 57% [55% to 59%] (colored target in the gray plateau) and 53% [51% to 55%] (gray target in the color plateau). Participants then adapted their target choices to the changing color ratio to some extent, although in a relatively weak form, with selection frequencies barely reaching 60% close to the plateaus (however, note that this is a range similar to that in Irons & Leber, 2016). In the informed-choice task, in which participants had been informed about the regularities and were encouraged to make use of them, color targets in the gray plateaus were selected with a probability of 83% [81% to 85%], and gray targets in the color plateaus with a probability of 82% [80% to 85%] (Fig. 4, lower panels). Participants thus selected the target whose color state was more unique in the display, a tendency that was strongest close to the plateaus and weaker toward the center of the transition, where presumably estimating the color ratio became more difficult.

The aggregated adaptation curves in Fig. 4 provide a coarse summary of the overall observer behavior. However, as Irons and Leber (2016) showed, there can be large individual differences in adaptive choice behavior. To deal with the greater noise on the individual data level, we applied the differentiated observer model described in the introduction. The posterior distributions of the mean AC and PSE estimates are visualized in Fig. 5.

The estimated mean AC parameters confirmed the presence of adaptation to the color state ratio in the free-choice

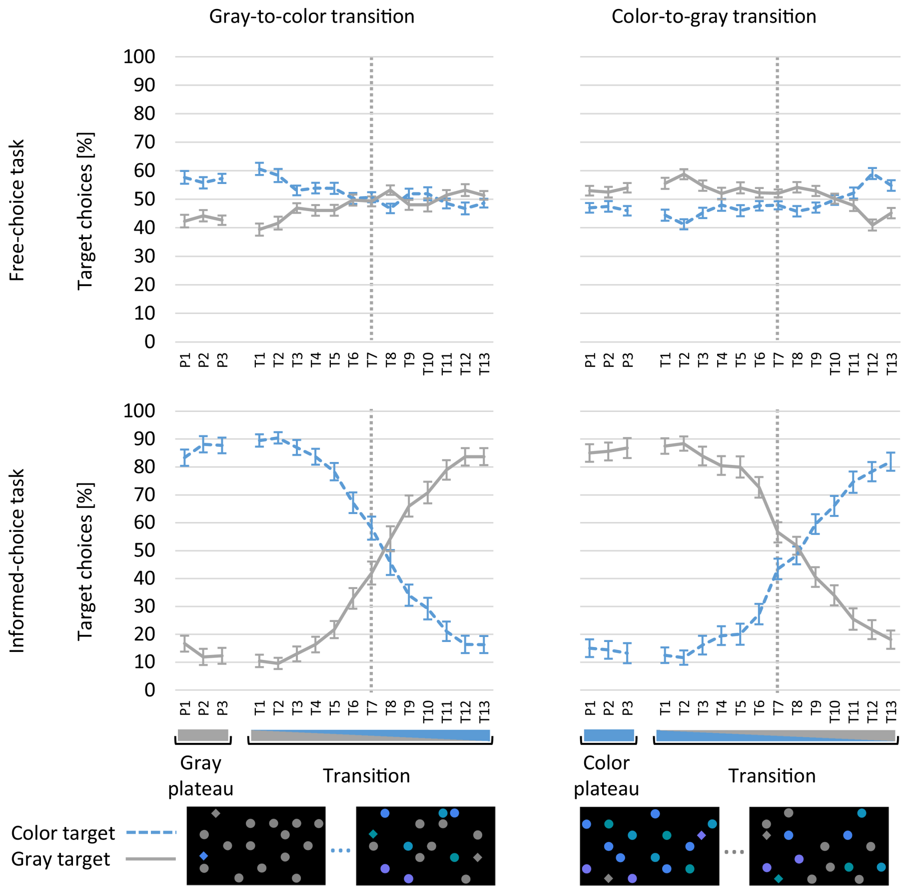

Fig. 4 Experiment 1: Target choices in the free-choice (upper panels) and informed-choice (lower panels) tasks, averaged across all participants, separately for the gray-to-color (left panels) and color-to-gray (right panels) transitions. Percentages of chosen colored targets are depicted as dashed lines, and gray targets as solid lines. Error bars depict the standard errors of the means.

task (see Fig. 5A). For both the gray-to-color and color-to-gray transitions, AC was estimated at .005 (and the difference between gray-to-color and color-to-gray was only .000019 [–.001 to .003]. The participant-level plots in Fig. 5C, which depict predicted adaptation curves and AC estimates, provide some intuition about the typical range of these values. To demonstrate that the estimated adaptation did not automatically result from the prior distributions and the model structure, we fitted simulated null-model data as a baseline (see the gray "Null-Sim" distribution in Fig. 5A). The null data were generated with a .5 probability of selecting either target (i.e., the equivalent to the flat line in Fig. 2). The difference between the baseline distributions estimated from the null data was .002 (with the HPD interval [.001 to .003] excluding "no difference" zero).

For the informed-choice task, AC was estimated at .32 [.25 to .41] for gray to color and .26 [.21 to .34] for color to gray. The difference between the two was .06 [–0.041 to 0.17], but zero was still within the HPD interval [– .41 to .01]. The AC estimates were substantially larger in the informed-choice than in the free-choice task. The lower 95% HPD boundaries on the differences were more than .2 above zero.

We additionally calculated correlations of the AC estimates and the Corsi and Stroop scores that were reported to relate to attentional control. We found no correlation for Stroop incongruence costs with AC estimates, in either the free-choice task or the informed-choice task. The Corsi block span, however, correlated with the individual AC estimates, but only in the gray-to-color transition in the free-choice task ($r = .43$ [.135 to .641], with a Bayes factor of 16.19 for the alternative hypothesis that the correlation is positive; one-sided test; see Fig. 6). Given that similar correlations were absent in the other task, the other transition direction, and all tasks and transition directions in Experiment 2, the presence of a correlation in this case should probably not be overinterpreted.

The PSE parameter models the subjective point at which selection was equally affected by both color states, with observers deciding for each target with a probability of 50%. As Fig. 5B shows, for the free-choice task, the PSE was slightly later than T7, which marks the transition trial in which both

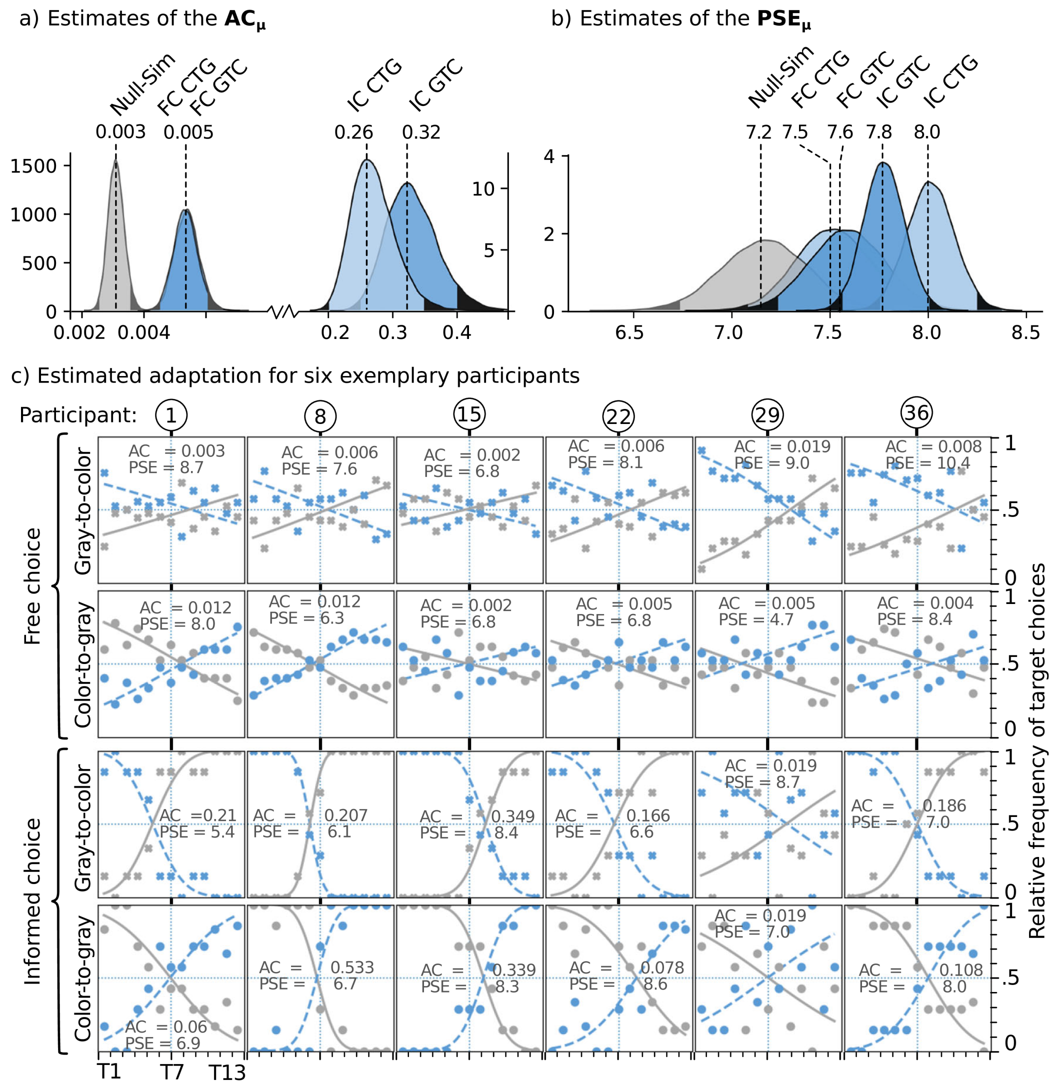

Fig. 5 (A) Posterior distributions of the adaptive choice (AC) estimates for the simulated null-baseline (Null-Sim) and the transitions from gray to color (GTC) and color to gray (CTG) for both the free-choice (FC) and informed-choice (IC) tasks. The dark tails of the distributions indicate the boundaries of the 95% highest probability density intervals. (B) Posterior distributions of the point-of-subjective-equality (PSE) estimates for the same conditions as in panel A. (C) Raw choice-frequency data and estimated adaptation curves for six exemplary participants for the CTG and GTC transitions in the FC and IC tasks.

color states were represented by the same number of distractors. For gray-to-color transitions, the PSE was located at 7.6 [7.2 to 7.9], and for color-to-gray, at 7.5 [7.2 to 7.9]. These estimates differed only marginally, by 0.24 [– 0.07 to 0.55], with zero lying inside the HPD interval. Only the PSE for gray-to-color differed substantially from the estimate from the simulated null data. For color-to-gray transitions, "no-difference" zero was still in the HPD interval (estimated as 0.48 [–0.06 to 1.09]), which was due to the broad distributions reflecting the uncertainty in the estimates.

In the informed-choice task, the PSE for gray-to-color transitions was estimated at 7.8 [7.6 to 8], and the one for color to gray at 8 [7.8 to 8.2]. The PSE of color to gray seemed to occur relatively late in this task. However, for the difference of 0.24, "no-difference" zero fell just inside the HPD interval [– 0.07 to 0.55]. Both PSE estimates differed substantially from the simulated null data.

Response times

Forced-choice task RTs in the forced-choice task were considered as a measure of search difficulty when searching for a single and defined target (i.e., either the colored or the gray target). The forced-choice RTs are depicted in Fig. 7A.

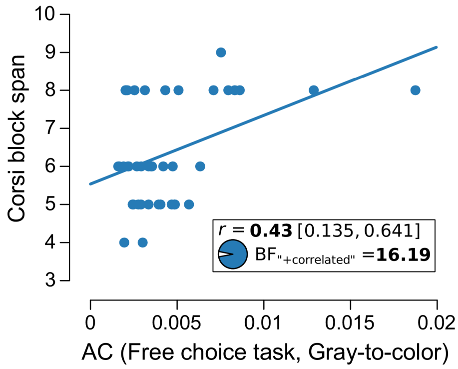

Fig. 6 Correlation between Corsi block span and adaptive choice (AC) for gray to color in the free-choice task. Note that if the highest two AC values were considered outliers and removed, *r* would change to .38 [.085 to .61], with a Bayes factor (BF) of 6.02 in favor of a positive correlation.

The analysis showed that search difficulty for either target depended on the number of distractors in similar color states in the display. Overall, performance was very accurate: An incorrect target was reported in 2.1% of trials, and a number not contained in the display in 1.8%. For statistical comparisons, the mean RTs in correct trials were pooled separately for transitions and plateaus (i.e., all data points within in a transition range, or plateau, were considered as independent samples). The fastest responses were observed for targets whose color state was unique in a plateau—that is, when searching for the colored target in the gray plateau (1,027 ms [1,000 to 1,053]) and for the gray target in the colored plateau (1,118 ms [1,090 to 1,148]). Responses were much slower when participants searched for the gray target in the gray plateau (difference from "color target in gray plateau": 175 ms [134 to 217]) or the color target in the color plateau (difference from "gray target in color plateau": 217 ms [169 to 265]); in both cases, zero, "no difference," is far outside the HPDs.

To quantify the impact of the changing color ratio on the efficiency of selecting either target, we estimated the slopes of the RTs and intercepts at T7. The search slopes and RTs at T7 during transition in forced choice are reported in Table 1. RTs were higher for colored than for gray targets (by 64 ms [42 to 86] in color-to-gray, and by 64 ms [43 to 86] in gray-to-color, transitions). All slopes showed the expected pattern: When the number of items that shared the target's color state became smaller, slopes were negative, reflecting the facilitation from having to inspect fewer items. When the number of items that shared the target's color state increased, slopes were positive, indicating increasing search difficulty.

Slopes in color-to-gray transitions showed that when coming from a colored plateau, the facilitation for a colored target by removing colored distractors was much stronger than the negative impact of adding gray distractors was for the gray target (the difference was 6.34 ms/item [2 to 10.8]; in gray to color, the difference was only 0.25 ms [−3.81 to 4.4]).

Figure 7A shows that the RT pattern for the gray and colored targets intersect far from the center of the transition. Estimating these intersection points on the basis of the RT_{T7} and slope estimates reported in Table 1 puts the intersection from gray to color at T3 (estimated at 2.9 [− 0.78 to − 4.8]), and the one from color to gray at T10 (estimated at 9.5 [8.5 to 10.5]). Keeping in mind that the gray-to-color transition began with a gray plateau and the color-to-gray transition led into one, this result shows that the intersections were shifted by more than two trials toward the gray plateau.

Free-choice and informed-choice tasks RTs in the free-choice and informed-choice tasks are depicted in Fig. 7B and C. Since these RTs were not of primary interest, they are shown for completeness but are not analyzed in detail. The overall pattern shows that in the free-choice task, RTs did not vary much over the trial sequence, whereas in the informed-choice task, they were more variable and increased toward the center of the transition. This RT increase could hint that target choice was most difficult at the center of the transition, likely because the color ratio was hard to estimate.

Discussion

The results of Experiment 1 showed that observers were tuning their attentional control settings toward the changing color state ratio even though color was not a target-defining dimension. Participants selected the colored target most frequently when it was unique, in the gray plateau, and the gray target when it was unique, in the color plateau. The AC estimates in the free-choice task showed that during the transition, participants shifted their target preference to the other target. PSE estimates further showed that the point at which participants became more likely to prefer the other target was near or shortly after the center of the transition. However, the results also revealed asymmetries in the AC behavior and the PSEs. Participants were better in adapting in the gray-to-color transition, in which they started by predominantly selecting the color target, than in the color-to-gray transition, in which they started by predominantly selecting the gray target. This was indicated by a later PSE and a smaller AC estimate in the color-to-gray transition. Although the HPD intervals suggested that these differences were rather uncertain, the color target seemed more likely to lead observers into target choice adaptation than the gray one.

To our surprise, we found no correlations of the AC estimates with known covariates of attentional control, except for the gray-to-color transition in the free-choice

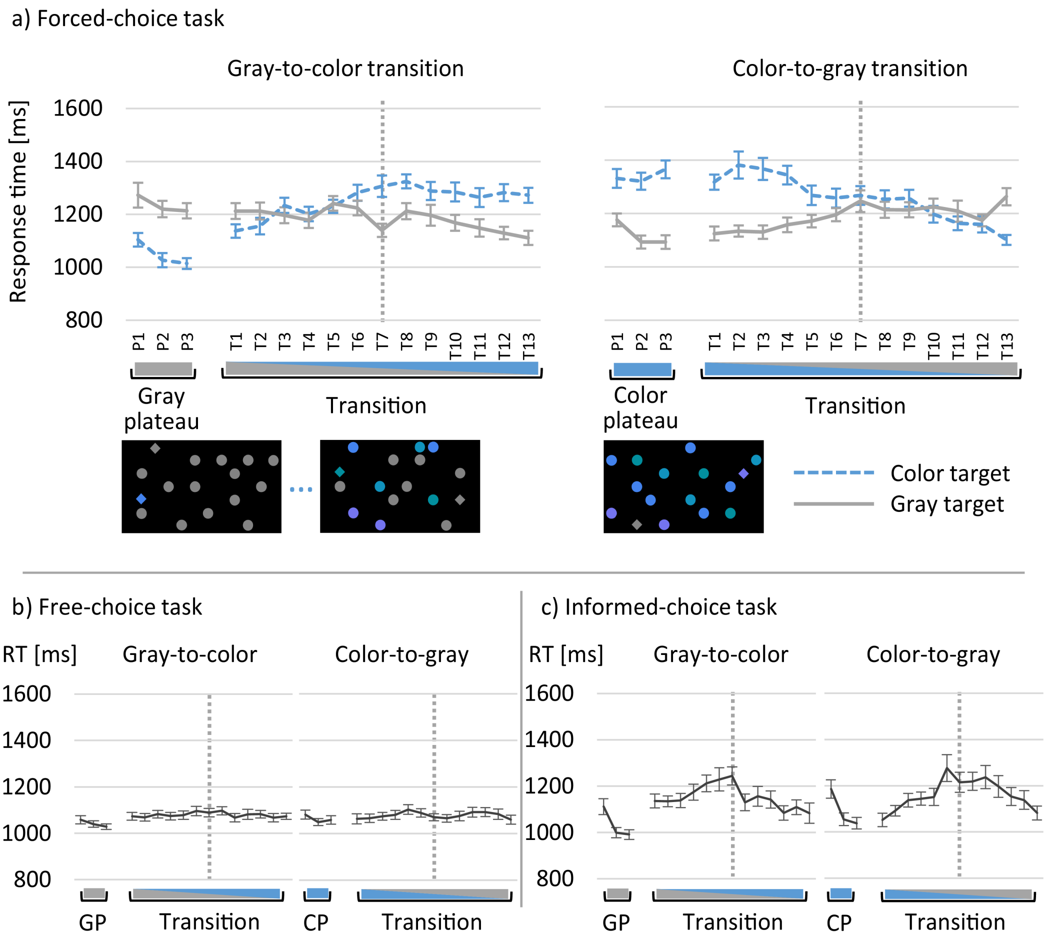

Fig. 7 Response times (RTs) in the forced-choice (A), free-choice (B), and informed-choice (C) tasks in Experiment 1. Results are shown separately for gray-to-color (left panels) and color-to-gray (right panels) transitions. For the forced-choice task (A), RTs for colored targets are depicted separately as dashed lines, and gray targets as solid lines. For the free-choice (B) and informed-choice (C) tasks, the general RT levels are displayed. Error bars depict the standard errors of the means.

task. In this transition, items of the same color state but heterogeneous in hue were added across trials. The heterogeneity in hue might have increased working memory demands, and capacity limitations thus might have had an impact on adaptive choice behavior. If so, this finding suggests that observers can adapt their choices with little effort when items of homogeneous hue (as in the gray color state) were added across trials, while adding items of heterogeneous hue hindered adaptation.

This consideration receives support from the RT pattern observed in the forced-choice task: RTs also showed asymmetries between gray-to-color and color-to-gray transitions, as evidenced by differences in the absolute slopes and intersection points of search for gray and colored targets (cf.

Table 1 Forced-choice task: Estimated means of the response times (RTs) at T7 and the search slopes for different targets and transitions in Experiment 1

Target	Transition	RT_{T7} [95% HPD]	Slope [95% HPD]
Colored	Color to gray	1,247 ms [1,231 to 1,264]	−17.63 ms/item [−21.67 to −13.45]
Gray	Color to gray	1,184 ms [1,169 to 1,198]	+8.2 ms/item [4.67 to 11.74]
Colored	Gray to color	1,242 ms [1,226 to 1,259]	+9.29 ms/item [5.21 to 13.56]
Gray	Gray to color	1,178 ms [1,164 to 1,192]	−6.85 ms/item [−10.37 to −3.34]

The 95% highest density intervals are stated in square brackets.

Fig. 7A). This suggests that hue heterogeneity might have influenced only target choices but also RTs when searching for either target.

Experiment 2

Some results of Experiment 1 suggested that hue heterogeneity of the colored distractors affected RTs (cf. Duncan & Humphreys, 1989; Feldmann-Wüstefeld & Schubö, 2013) and AC behavior. In Experiment 2, we therefore used items of homogeneous hues whose color state changed dynamically from red to blue. For each trial sequence, two particular hues of each color (i.e., a particular red and blue hue) were chosen (see Fig. 8 for the trial sequence and exemplary search displays in Exp. 2). We expected that using homogeneous hues in changing color states would balance the effort needed, and result in an increasing adjustment of target choices to the changing color ratio.

Method

Participants

Forty new volunteers (27 female, 13 male), naive to the paradigm and objective, participated for course credit or payment. The participants were between 19 and 30 years old (*M* = 22.5, *SD* = 2.65) and had normal or corrected-to-normal visual acuity and normal color vision (both tested with Oculus Binoptometer 3). Participants attested written understanding and consent before the experiment started. The experiment was conducted in accordance with the ethical standards of the Declaration of Helsinki and was approved by the Ethics Committee of the Faculty of Psychology at Philipps-University Marburg.

Apparatus and stimuli

The apparatus and stimuli were identical to those of Experiment 1, except that the stimuli were now red and blue. The exact hues of both colors were constant during one experimental block but varied randomly across blocks. For each block, one of four possible hues was selected in the range of the colors red and blue. The four blue hues were the same as in Experiment 1 (RGB 0, 170, 136; 18, 152, 197; 64, 131, 237; and 111, 111, 240). The four red hues were determined by rotating the blue hues from Experiment 1 by 180° in the color space (HSV) and matching the new colors in luminance (RGB 255, 88, 47; 236, 92, 45; 179, 118, 17; and 130, 130, 13). As in Experiment 1, one target was always blue; the other was always red, and the ratio of red and blue distractors dynamically varied throughout the trial sequence (see Fig. 8).

Procedure and data analysis

The experimental procedure was identical to that in Experiment 1, except that all tasks were performed on a single day. Target choices, RTs, and individual differences were analyzed as in the analysis of Experiment 1.

Results

Target choices

Free-choice and informed-choice tasks We found stronger adaptation in this experiment than in Experiment 1 in both the free-choice and informed-choice tasks. Also in Experiment 2,

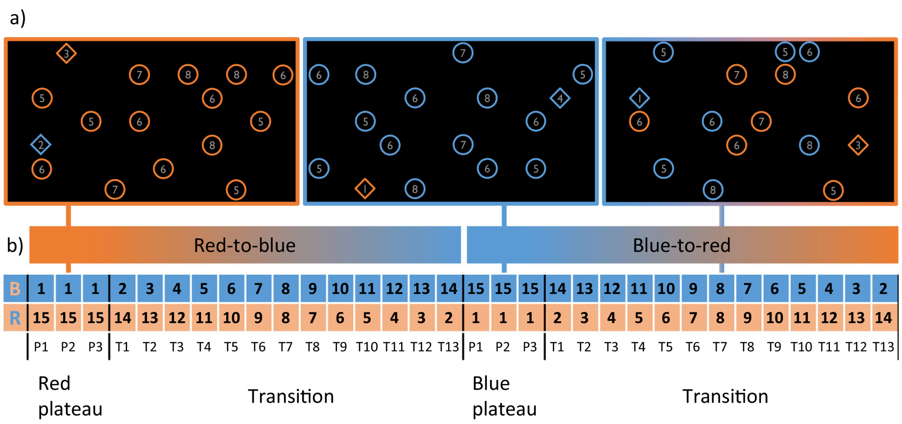

Fig. 8 Exemplary search displays and trial sequence in a block of Experiment 2. The search display always contained two shape targets (diamonds) and 14 distractors (circles). One target was always red, and the other always blue. The proportions of red and blue distractors transitioned from red plateaus (no blue distractors: A, left display) to blue plateaus (no red distractors: A, middle display). Panel B shows the numbers of red ("R") and blue ("B") items in the display in each trial.

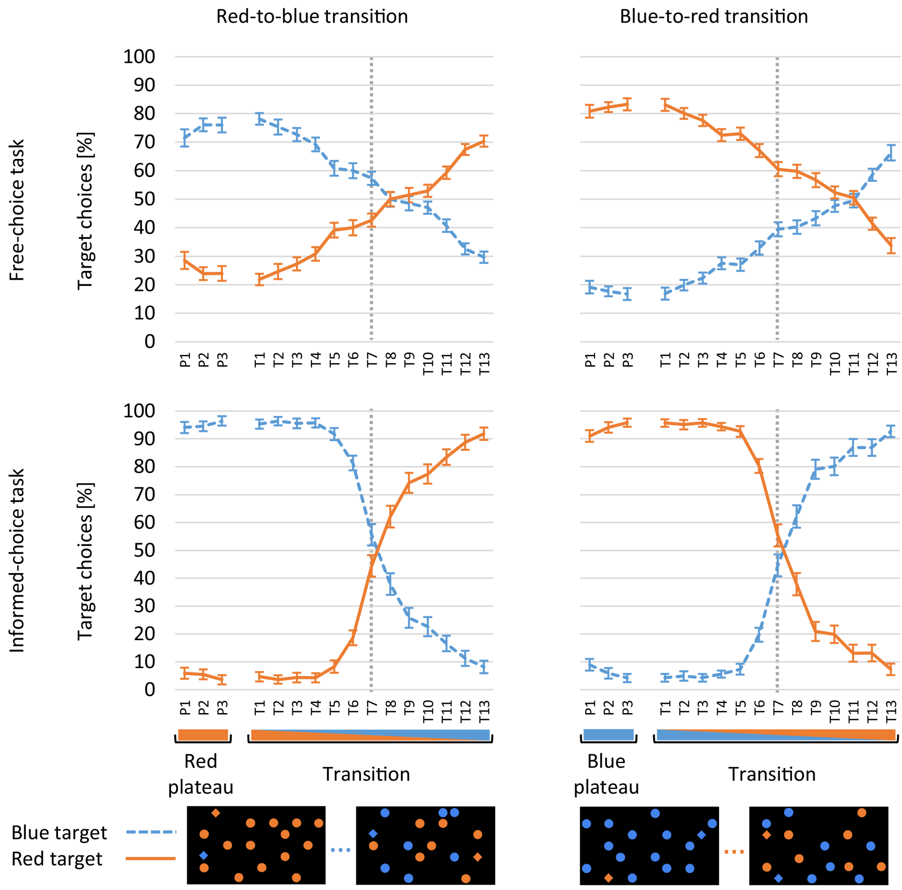

Fig. 9 Target choices in the free-choice (upper panels) and informed-choice (lower panels) tasks in Experiment 2, averaged across all participants separately for the red-to-blue (left panels) and blue-to-red (right panels) transitions. Percentages of chosen blue targets are depicted as dashed lines, and red targets as solid lines. Error bars depict the standard errors of the means.

participants showed stronger adaptation in the informed-choice than in the free-choice task, which can be seen in Fig. 9.

In the free-choice task, the red target was selected with a probability of 81% in the blue plateaus [78% to 83%], and the blue target with a probability of 73% [72% to 75%] in the red plateaus. In the plateaus of the informed-choice task, in which the participants were encouraged to adapt, the target unique in color was selected with a probability of 90% [88% to 92%] for blue among red and 91% [89% to 93%] for red among blue.

For a differentiated analysis of the AC behavior, we applied the same model with the same priors as in Experiment 1. The estimated posterior distributions are depicted in Fig. 10. In the free-choice task, AC was estimated at .024 for both transitions, thus differing strongly from that of the simulated null data (the difference was .02 [.018 to .023]). The AC estimates were similar for both transition directions; the difference was only .0004 [– .0027 to .0036]. This was far from the sizes in the informed-choice condition, for which the values were estimated at .55 [.45 to .66] for red to blue and .62 [.52 to .75] for blue to red. However, in Experiment 2 both the free-choice and informed-choice AC estimates were substantially larger than in Experiment 1. A direct comparison across experiments confirmed the higher ACs in Experiment 2: free choice, .019 higher [.017 to .02]; informed choice, .289 higher [.195 to .384]. The participant-level plots in Fig. 10C show that the participants in Experiment 2 reached the convergence levels earlier (close to the center of the transition), whereas in Experiment 1 the participants had reached them later (closer to the plateaus), if they reached them at all.

In the free-choice task, the PSE estimate was located at 8.0 [7.8 to 8.2] for the red-to-blue transition, and at T9 in the blue-to-red transition (estimated at 9.5 [9.2 to 9.7]). In the informed-choice task, both PSE estimates were located around T8 (red to blue, 7.9 [7.8 to 8.0], blue to red, 7.8 [7.7 to 7.9]). All PSE estimates differed clearly from the simulated null-data PSE at 7.2 (all lower 95% HPD boundaries of the difference were at 0.18 or higher).

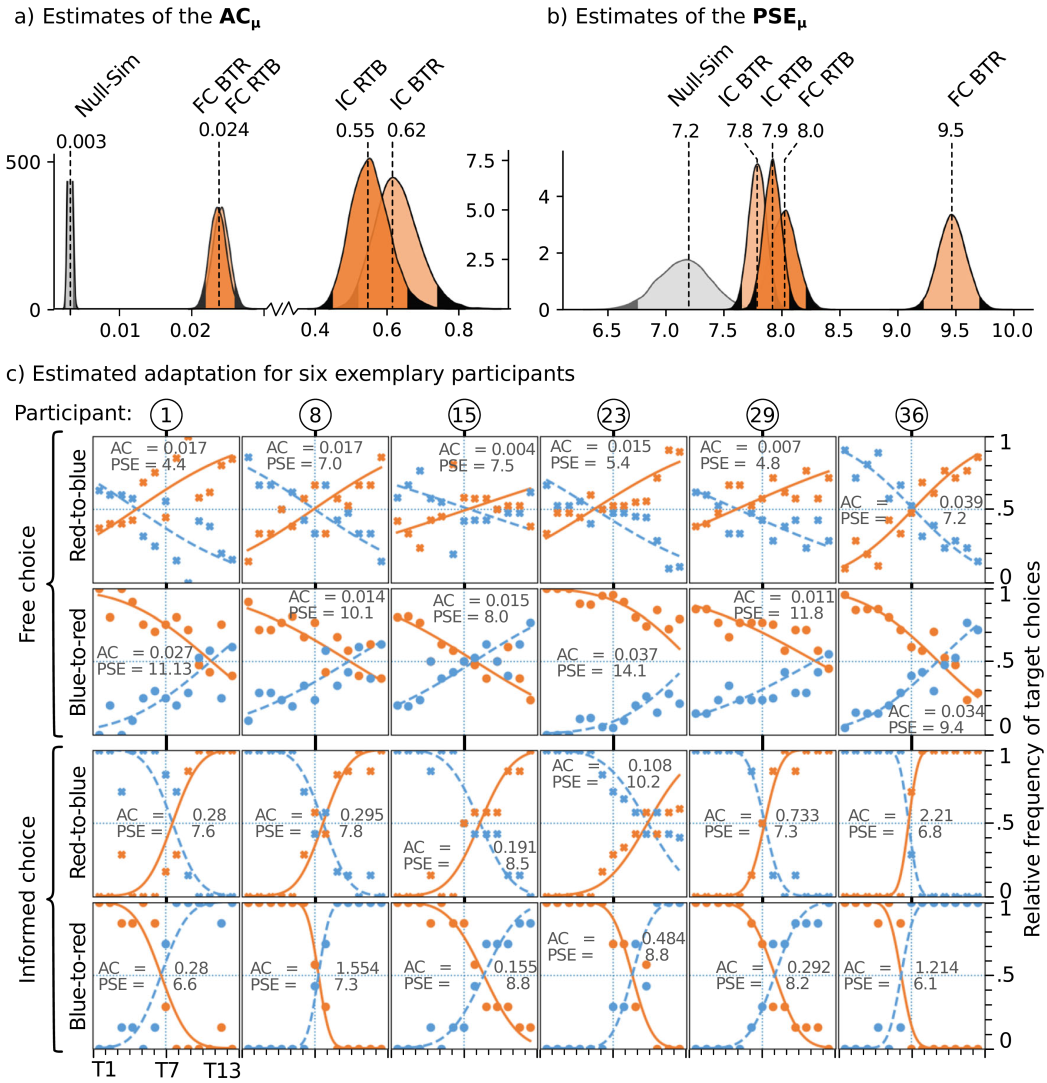

Fig. 10 (A) Posterior distributions of the adaptive choice (AC) estimates for the simulated null baseline (Null-Sim) and the transitions from red to blue (RTB) and blue to red (BTR) for both the free-choice (FC) and informed-choice (IC) tasks. The dark tails of the distributions indicate the boundaries of the 95% highest probability density intervals. (B) Posterior distributions of the point-of-subjective-equality (PSE) estimates for the same conditions as in panel A. (C) Raw choice-frequency data and estimated adaptation curves for six exemplary participants for the RTB and BTR transitions in the FC and IC tasks. The participants were selected arbitrarily (equally spaced participant numbers), except for Participant 23, who was selected as an example of the strong red bias a few participants showed.

Response times

Forced-choice task RTs in the forced-choice task are shown in Fig. 11A. As in Experiment 1, the RTs increased with the number of distractors in the same color states. However, in contrast to Experiment 1, this effect was symmetric, showing similar increases for targets of either color state.

In the plateaus, responses to the target unique in color state were faster: RTs were on average 964 ms [922 to 1,008] for the red target in the blue plateaus, and 411 ms slower [347 to 475] when the blue target was selected in the blue plateau. For blue targets in the red plateau, the average RT was 969 ms [935 to 1002], whereas participants responded 439 ms [361 to 512] slower in the “red among red” plateau.

As in Experiment 1, search slopes during transition and RTs at T7 were estimated (cf. Table 2). In contrast to Experiment 1, the RT_{T7} estimates of the two target colors during transition were only slightly different (mean difference for blue to red estimated at 11 ms, “no-difference” zero still inside the 95% HPD interval [−11 to 33]; mean difference for red to blue estimated at 27 ms [−50 to −5]). Again, the slopes showed the expected pattern: The slope

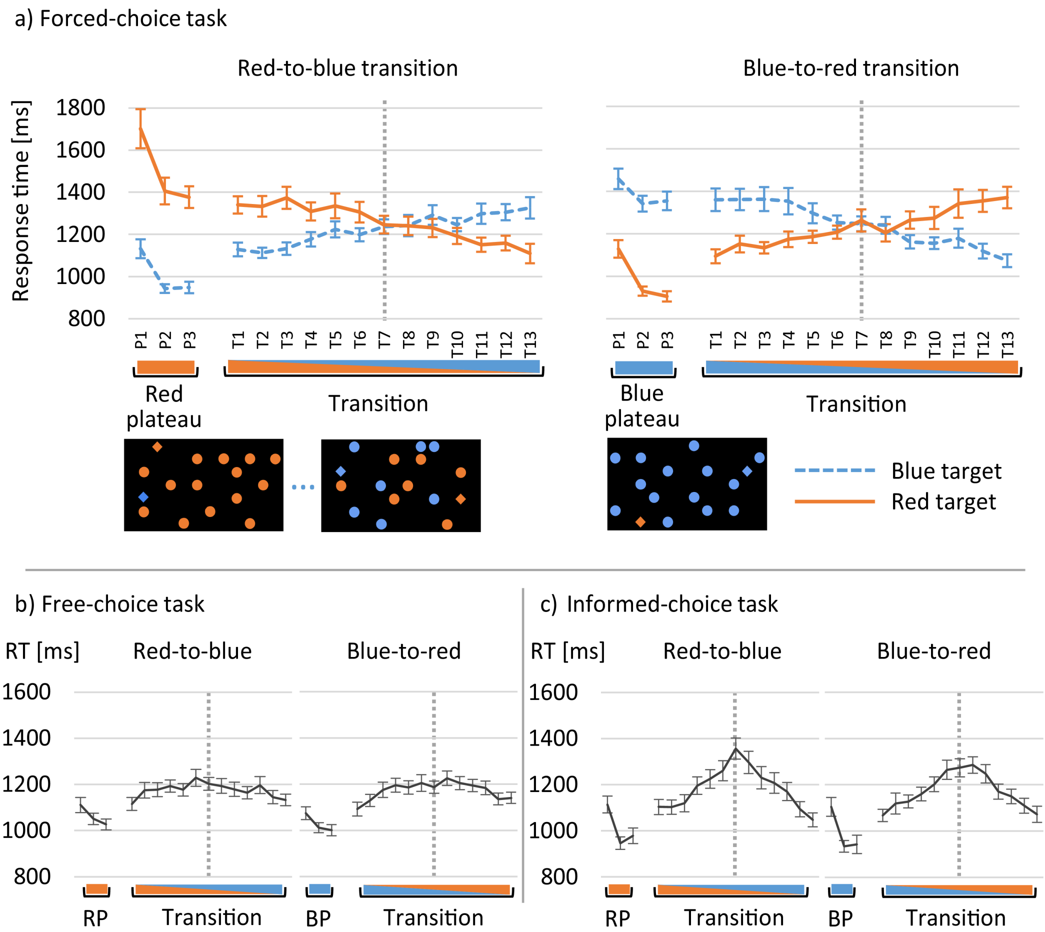

Fig. 11 Response times (RTs) in the forced-choice (A), free-choice (B), and informed-choice (C) tasks in Experiment 2, separately for red-to-blue (left panels) and blue-to-red (right panels) transitions. For the forced-choice task (A), RTs for blue targets are shown separately as dashed lines, red targets as solid lines. For the free-choice (B) and informed-choice task (C), the general RT level is displayed. Error bars depict the standard errors of the means.

was negative when the number of items that shared the target's color state was reduced, and positive when the number increased. The estimates of the absolute slopes within one transition differed only slightly, and not beyond the uncertainty in the estimate: For blue to red, the slope was 2.81 ms/item steeper for the blue than for the red targets, but the 95% HPD interval [−1.86 to 7.7] left much doubt about the presence and direction of a difference. For red to blue, the blue target's slope was slightly steeper (by 3.42 ms/item, [−1.24 to 8.19], again reflecting no substantial difference).

In stark contrast to Experiment 1, the estimated intersection points of the search curves (see Fig. 11A) were close to the center of the transition. In the red-to-blue transition, the intersection was at T8 (estimated at 7.81 [7.12 to 8.52]), and for blue to red, at T7 (estimated at 7.27 [6.71 to 7.83]), indicating

Table 2 Forced-choice task: Estimated means of the response times (RTs) at T7 and search slopes for different targets and transitions in Experiment 2

Target	Transition	RT_{T7} [95% HPD]	Slope [95% HPD]
Blue	Blue to red	1,232 ms [1,216 to 1,248]	−21.82 ms/item [−25.67 to −17.95]
Red	Blue to red	1,221 ms [1,205 to 1,236]	+18.64 ms/item [14.81 to 22.52]
Blue	Red to blue	1,216 ms [1,201 to 1,231]	+15.57 ms/item [11.68 to 19.34]
Red	Red to blue	1,243 ms [1,227 to 1,260]	−18.14 ms/item [−22.3 to −14.03]

The 95% highest density intervals are given in square brackets.

that searching for red or blue targets was similarly difficult in displays with homogeneous hues. Therefore, and in contrast to Experiment 1, the RT pattern was symmetric with respect to T7.

Free-choice and informed-choice tasks RTs in the free-choice and informed-choice task are shown in Fig. 11B and C. In the free-choice task, RTs seemed to increase toward the center of the trial sequence. This pattern looks even more pronounced in the informed-choice task, as there seems to be a sharp peak of RTs at trial T7.

There was also a difference in RTs in the free-choice tasks between the two experiments. Responses in Experiment 2 were on average 77 ms [15 to 135] slower than those in Experiment 1. RTs in the informed-choice task differed by 13 ms [– 59 to 82] from Experiment 1, but with "no-difference" zero inside the interval.

Discussion

Experiment 2 was similar to Experiment 1, except that homogeneous distractor hues were used, as we expected homogeneous hues to facilitate the adaptation of choice behavior. We replicated the finding of Experiment 1 and found that participants adapted their target choices to the changing ratio of color states, although color was not required in order to find one of the targets. AC behavior was clearly more pronounced than in Experiment 1, reflected in much larger AC estimates in the free- and informed-choice tasks. Homogeneity in hues seemed to have facilitated spontaneous grouping of stimuli (Duncan & Humphreys, 1989), which fostered the adaptation of choice behavior to the dynamically changing ratio of color states.

Most PSEs were estimated to be close to T8 (similar to Exp. 1), indicating that on average observers' internal estimates of the color state ratio lagged slightly behind the objective ratio of items in one or the other color state. A very large PSE was estimated for blue-to-red transitions in the free-choice condition. That is, when participants started with selecting the red target in blue plateaus, they tended to stick much longer with this preference than they did in the opposite condition. However, our findings did not reveal a similarly strong PSE shift in the opposite direction (indicating an early switch to red) when participants started with selecting blue in the red plateau.

In contrast to Experiment 1, similar search slopes and RTs at T7 were observed for both target color states in both transitions in the forced-choice task. The intersection points at which searching for red was equally fast as searching for blue were now close to the center of the transition. This shows that search efficiency was affected similarly for both targets when items were added from a different color state. In sum, our AC, PSE, and RT results showed that using homogeneous hues for both color states removed the search asymmetries and facilitated the adaptation of choice behavior to the changing color state ratio.

Individual differences in the point of subjective equality in Experiments 1 and 2

Up to here, we have discussed the averaged behavior, and AC estimates indicated that adaptation was present in Experiment 1 but stronger in Experiment 2. The mean PSE estimates, however, provided not much insight, beyond the fact that participants lagged slightly in updating their internal color ratio estimates. For a more differentiated analysis of the PSEs, we fitted the observer model at the participant level. In particular, we correlated the individual estimates from the different transition directions (gray to color vs. color to gray and red to blue vs. blue to red). Positive correlations indicate that the predominant factor determining interindividual variation was how long observers stayed with targets in the color state they started with, irrespective of the particular target color and transition direction. Negatively correlated PSEs would occur if individual differences were predominantly determined by preferences for targets in a particular color state, even if they occurred in the larger color set.

For Experiment 1 we found no evidence for such correlations (see Fig. 12, top panels), most likely due to a high level of noise in the estimates (which was also reflected in the broad posterior distribution in Fig. 5B). However, in Experiment 2 both negative and positive correlations occurred, depending on the task (see Fig. 12, bottom panels). In the free-choice task, the PSEs were correlated negatively, indicating that variability in PSEs was determined by individual preferences for the red or the blue target. As can be seen in the scatter plot, two participants stayed especially long with preferring the red targets (when starting from the blue plateau). They stayed with it so long that their PSE estimates were even larger than 13, outside the actual trial range. Such extreme cases might have driven much of the very large mean PSE estimate for blue to red depicted in Fig. 10B.

In the informed-choice task, in which participants were encouraged to adapt their target choices, the PSEs correlated positively (note, however, that the Bayes factor is below 3, which sometimes has been referred to as "anecdotal evidence" only). The scatter plot shows that most PSEs cluster rather close to T7, but a few participants had the tendency to select the target of the color state they had started with for as long as until T10 and T11.

The pattern of results in Experiment 2 hints that when adapting to a regularity implicitly learned during the task (free choice), individual preferences (as for particular colors) were

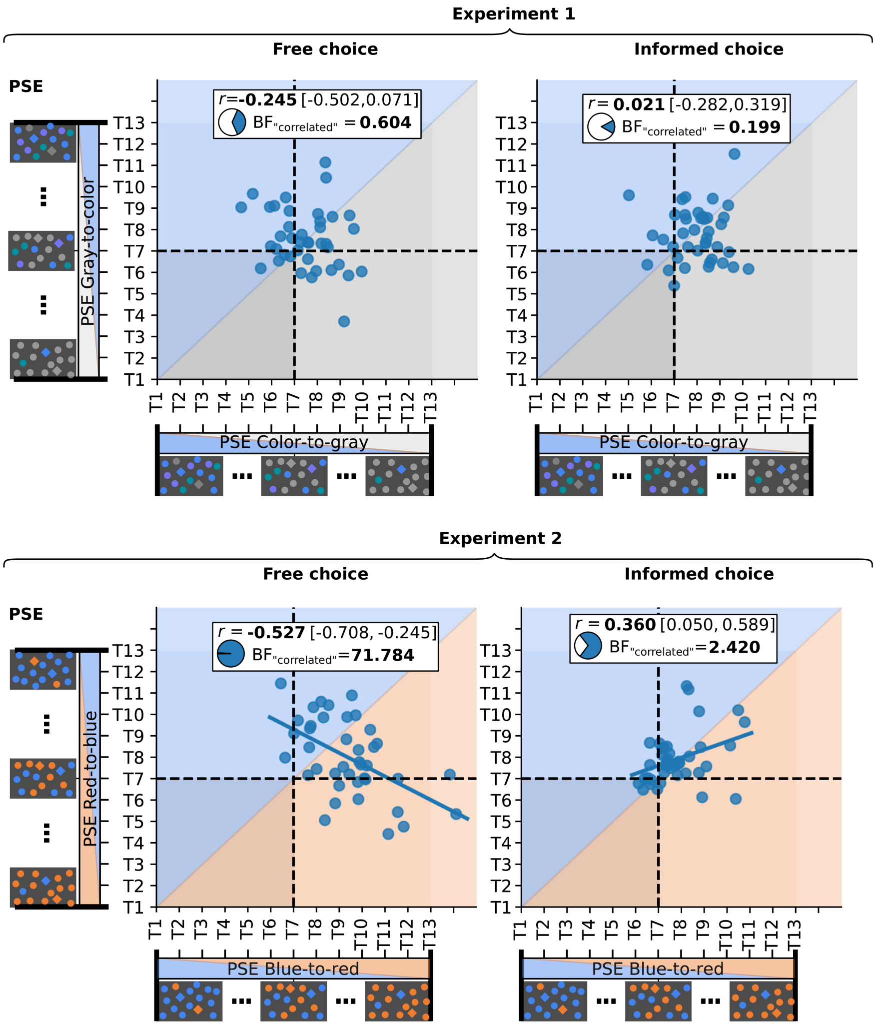

Fig. 12 Correlations of the points of subjective equality (PSEs; the modes of the individuals' posteriors were taken as point estimates) between transition directions. The insets state Pearson correlation coefficients, with Bayesian 95% highest probability density intervals in square brackets. The Bayes factors (BFs) indicate how many times a correlation was more likely than no correlation.

the main cause for deviations from the "ideal-observer" switching point. When performing with explicit information (informed choice), such preferences might have been inhibited in favor of a general tendency to stay longer with the initially selected target. Note that both behaviors could have been manifestations of target switch avoidance, reported by Irons and Leber (2016) as a strategy employed by "effort minimizers."

General discussion

In this article, we studied the adaptation of attentional selection in a visual search task in a dynamically changing environment. We conducted two experiments, in which two shape singleton targets were present in every trial. Participants were free to select either of the targets. The targets could be in one of two color states and were presented among 14 circle distractors whose color state changed systematically across trials. The color state varied dynamically from one plateau in which one target (e.g., blue) was the only blue item in the display (and thus unique in its color state), to the other plateau in which the other target was the only uniquely colored item. These plateaus were connected by transition phases in which the ratio of distractors in one or the other color state gradually changed, as one of the distractors changed its color state (e.g., from red to blue) in each trial. Although color was not required to find one of the shape targets, we hypothesized that participants would adapt their target choice to the changing color state ratio by selecting the target from the color state of the smaller subset, and that they would change their preference during the trial sequence when the ratio of the color states reversed.

The results showed that participants adapted their target choices to the changing color ratio. During the plateaus, they preferred selecting the target unique in color state, and switched to selecting the other target when the color ratio gradually changed. This adaptive choice behavior was visible in Experiment 1, in which the color states were "colored" and "gray," and was even more pronounced in Experiment 2, in which color states were "red" and "blue" and homogeneous hues were used. Estimated PSEs showed that participants inverted their target preference later than in trial T7, the trial in which both color states comprised the same number of distractors. An additional analysis of PSEs reported above revealed that this tendency was not only due to a delayed updating of the target preference in general but also to individual preferences for one or the other color state.

In both experiments, participants responded slower toward the center of the transition (T7) when informed about the changing distractor color ratio, and when thus encouraged to adapt their behavior accordingly. Although these RTs were not our primary dependent variable, but rather were assessed as a control, this RT slowing points to an interesting aspect: It indicates that task demands might have differed when participants had been asked to adapt on purpose. Adapting on purpose required preparing actively for an upcoming trial—for instance, by estimating the color ratio and updating attentional control settings. Such active preparation is known to require proactive control (e.g., Braver, 2012). Proactive control might have led to a more accurate adaptation, but it also slowed responses, especially around trial T7 when the number of items in each color state approached equality and it became more difficult and therefore time-consuming to determine the smaller subset.

As a reference for the impact of gradually changing color states on target search, we conducted an additional forced-choice task that mirrored more "standard" visual search tasks. When participants had to select a particular target (e.g., the blue target) throughout the trial sequence, RTs increased with each additional distractor sharing the target's color state, thus mimicking slopes of classical (RT × Set Size) functions in visual search.

Relationship to Irons and Leber's (2016) results

Our findings replicate the results of Irons and Leber (2016), that observers adapt to gradually changing regularities in visual search when choosing one of two targets. As in the original paradigm, participants adapted target choice to a gradual color change in the trial sequence and showed a tendency to select the target from the smaller color subset.

Note that the experimental design used in the present study differed from the original task in an important aspect. In the studies by Irons and Leber (2016, 2018), the targets were either blue or red. The color change of the distractors in the display was insofar relevant, as color was a target-defining dimension. In our paradigm, the dynamical color change was decoupled from the target-defining shape feature, as color was not a required feature to find the target. Furthermore, we instructed our participants differently: In Irons and Leber's initial (2016) experiment, the authors informed their participants that the targets were smaller in size and red or blue, and told them that they may find it easier to search for the color shared by fewer objects in the display. In the free-choice task in our study, participants were neither informed that the targets differed in color, nor that the distractor colors changed across trials. Our results therefore show that observers not only adapt to changing distractor colors when color is a relevant target-defining dimension, but also when color is not necessarily required in order to find a target. In other words, choice behavior was affected by a dynamic yet irrelevant change in the color state ratio, simply by its presence.

Adapting to color when searching for shape

Why did participants adapt their behavior to color if they could have performed the task by only searching for the shape singletons? Perhaps color was difficult to ignore: Adapting target choice to color was efficient in the plateaus, since the unique color state of one target in the starting plateau allowed for fast and spontaneous processing of this item (cf. Theeuwes, 1992; Treisman & Gelade, 1980). Uniquely colored items are known to result in attentional capture even when participants intend to search for shape, an effect well-known from the additional-singleton literature (Theeuwes, 2004, 2010, 2013, 2018). Once being captured toward a particular color feature, participants might have considered the color dimension helpful for finding the target. Dimensions are known to play an important role in target selection in visual search (cf. Krummenacher & Müller, 2012; Müller, Heller, & Ziegler, 1995). Moreover, attentional weights assigned to a single color feature can generalize to the entire color dimension (Feldmann-Wüstefeld, Uengoer, & Schubö, 2015; Müller, Reimann, & Krummenacher, 2003). The dimensional weighting account assumes that assigning attentional weights to particular dimensions not only leads to facilitated processing of the weighted dimension in visual search. Since capacity is limited, up-weighting one dimension entails down-weighting others (Krummenacher & Müller, 2012; Müller et al., 1995). Following this logic, one could speculate that assigning some attentional weight to the color dimension in our paradigm has resulted in down-weighting of the shape dimension, which might have enhanced the impact of color not only in plateaus but also during transition phases.

Alternatively, observers might have used the changing ratio of color states in a less explicit, and more passive and spontaneous, way. Observers are known to spontaneously extract statistical regularities in the environment for determining attention guidance, a process that is referred to as statistical learning (Failing & Theeuwes, 2018; Theeuwes, 2018, 2019). For instance, observers rather implicitly exploit invariant contextual information in visual search when these regularities can be used to facilitate target detection, especially when encountering similar contexts again (Chun & Jiang, 1998; Goujon, Didierjean, & Thorpe, 2015). For finding the target, learning of such contextual information can be highly relevant. Recent studies also demonstrated statistical learning of rather irrelevant environmental regularities. Several studies have shown that statistical regularities regarding the location of irrelevant color distractors influenced attentional capture, although observers were searching for shape targets. Similar to our findings, using such regularities was occasionally detrimental to task performance (Ferrante et al., 2018; Wang & Theeuwes, 2018a, 2018b, 2018c; see also Sauter, Liesefeld, & Müller, 2019; Sauter, Liesefeld, Zehetleitner, & Müller, 2018). Participants in our paradigm also adapted their choices to the regularly changing distractor color ratio. They did so despite the fact that ignoring color and selecting the target with the help of a shape template might have been a more efficient search strategy: In their article on visual marking, Watson and Humphreys (1997) suggested that observers generate a target template to guide their selection throughout the trial sequence. According to this notion, participants would have been able to simplify their search remarkably in our paradigm by establishing an (inhibitory) template based on the target-defining dimension. In doing so, the number of to-be-selected items would have been reduced to those two items in a trial that matched the target-defining dimension. Although also taking color into account might have been more efficient than focusing on shape alone on *some* trials, establishing a shape template would have provided an immense benefit in *every* trial.

Interestingly, our results showed more pronounced adaptation when the distractor colors were homogeneous in hue, as was reflected in the larger AC estimates in the free-choice and informed-choice tasks in Experiment 2. We assume that homogeneity in hue facilitated similarity-based grouping; that is, grouping of distractors in the same color state. According to Duncan and Humphreys (1989), items that share the same basic feature can be linked into a single perceptual unit, a grouping process that is spontaneous and requires no attentional control. Such spontaneous grouping of similar items was possible for both color states in Experiment 2, what might have facilitated adapting target selection to changing color states similarly in both transitions (i.e., red-to-blue and blue-to-red transitions) between plateaus. In Experiment 1, however, heterogeneity in one of the color states seemed to have hindered grouping, resulting in several asymmetries in performance in gray-to-color as compared to color-to-gray transitions. Following this consideration, we assume that observers can easily adapt to changes that can be registered spontaneously and without attentional control, whereas changes that increase the demand for attentional resources lower adaptive behavior.

It is not surprising that the spontaneous adaptation was lower in the free-choice than in the informed-choice task, in which participants were encouraged to adapt: A host of factors might have fostered a balanced selection of both target types across the trial sequence. For instance, even though target positions were randomized and their eccentricity was matched, spatial configurations occurring by the random placement of the distractors might have promoted the selection of one target irrespective of its color. Beyond such random influences from display configuration, there might have been conflicting components of participants' overall search strategies—for instance, a tendency to select both target types equally often. Importantly, despite such influences that would drive the adaptation curves toward chance level, we still detected the signature pattern of adaptation in all tasks of both experiments, confirming that participants always incorporated statistical regularities of the displays into their behavior.

It is known that learning statistical regularities cannot only guide attention to specific spatial *locations* (e.g., Ferrante et al., 2018), but also influence processing of target *features* (Cosman & Vecera, 2014). Our results add to these findings by revealing that statistical learning not only takes place when *target* features exhibit regularities, but also when nonrelevant *distractor* features change in a regular manner. Our experiments also show that statistical learning takes place even when learning is not resulting in an overall reduction of RTs.

From a broader perspective, the extraction of regularities from the environment seems to be deeply rooted in biological organisms. The same might hold for spontaneous adaptation toward regularities, especially since they are often (although not always) beneficial for behavior. Superstitiously spinning pigeons in Skinner boxes are just one curious example (e.g., Morse & Skinner, 1957). After completing our experiments, we asked participants whether they had noticed any regularities. We obtained answers that described patterns that were elaborately complex but that were, in fact, not there. For instance, one person stated that "[a]fter a series of stimuli in the same place, the side was changed or the stimulus was shown more hidden." When investigating adaptive choice visual search and other behaviors that draw on statistical learning, one should keep in mind that observers integrate environmental regularities into their behavior in versatile ways, which may not necessarily relate to (global) optimality criteria, posing a challenge for ideal-observer models and similar approaches.

A model-based assessment of adaptive choice visual search

In contrast to earlier adaptive choice visual search studies, this study employed a model-based approach. Borrowing a sigmoid function usually used for more restrictive psychophysical tasks, we modeled how observers adapted their target choice to the changing ratio of the items' color state. The model allowed estimating the precision with which observers selected targets from the smaller color subset, a parameter we took as an index of AC behavior. Estimation of the PSE quantified how many trials participants lagged behind in updating their internal representation of the changing color ratio. Although this observer model leaves open the reason for low or high ACs and shifted PSEs, it summarizes adaptation quantitatively on the participant level. This is an important step forward, relative to earlier approaches that have discussed the shape of adaptation curves qualitatively and averaged across many observers. Moreover, our model provides an interface for Bayesian parameter estimation, which allows for describing the observed behavior and the uncertainties at all levels and enables assessing differences between experiments, tasks, and observers.

That the model-based approach can lead to behavioral insights that are more fine-grained than those based on average adaptation curves can be seen in our findings concerning the delayed switching points: Similar to the participants in Irons and Leber's (2016, 2018) studies, our participants tended to switch their target preference later in the transition than expected. Irons and Leber (2016) argued that late switching might be due to effort minimization, since it might be less effortful to search for the same target as in the previous trial. In the present study, a correlation analysis of participant-level PSE estimates (which reflect the switching points) hints that there might have been further reasons for switching at locations other than the center of the transition. Performance in the free-choice task of Experiment 2 showed that some participants had a bias for a particular color; for instance, they stayed unexpectedly long with red targets in blocks that started with blue plateaus. Although this behavior does not contradict effort minimization, it might also result from individual preferences (e.g., Fortier-Gauthier, Dell'Acqua, & Jolicœur, 2013).

By applying a parametric data model, the present approach constitutes a first step in exploring AC visual search data from a model-based perspective. In future work this model could be extended toward a more fine-grained, process-based model. This might help to disentangle set size discrimination ability from other influences on adaptation strength.

Conclusion

The present study has demonstrated that observers adjusted their attentional control settings to gradually changing regularities in the distractor colors although they were not instructed to do so, nor was the change needed to accomplish the task. These results show that observers extract regularities from their environment and spontaneously use this information in their behavior. The observers did so even though they did not seem to benefit, in terms of search speed. On the contrary, increasing RTs toward the transition center hint that adapting occasionally even had a negative impact on performance. One conclusion from these results is that observers can easily adapt to changes at the feature level, which are registered spontaneously and without attentional control. Observers can do so even though there might be other, more obvious strategies for selecting the target, such as focusing on shape singletons in the present study. These findings add to the growing body of studies reporting the influence of statistical learning of nontarget features on attentional control.

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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*, 437–443. https://doi.org/10.1016/j.tics.2012.06.010

Bacon, W. F., & Egeth, H. E. (1994). Overriding stimulus-driven attentional capture. *Perception & Psychophysics*, *55*, 485–496. https://doi.org/10.3758/BF03205306

Botvinick, M., & Braver, T. (2015). Motivation and cognitive control: From behavior to neural mechanism. *Annual Review of Psychology*, *66*, 83–113. https://doi.org/10.1146/annurev-psych-010814-015044

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

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. *Cognitive Psychology*, *36*, 28–71. https://doi.org/10.1006/cogp.1998.0681

Cosman, J. D., & Vecera, S. P. (2014). Establishment of an attentional set via statistical learning. *Journal of Experimental Psychology: Human Perception and Performance*, *40*, 1–6. https://doi.org/10.1037/a0034489

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*, 433–458. https://doi.org/10.1037/0033-295X.96.3.433

Egeth, H. E., Virzi, R. A., & Garbart, H. (1984). Searching for conjunctively defined targets. *Journal of Experimental Psychology: Human Perception and Performance*, *10*, 32–39. https://doi.org/10.1037/0096-1523.10.1.32

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

Feldmann-Wüstefeld, T., & Schubö, A. (2013). Context homogeneity facilitates both distractor inhibition and target enhancement. *Journal of Vision*, *13*(3), 11. https://doi.org/10.1167/13.3.11

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*, 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*, 847–858. https://doi.org/10.1037/0096-1523.24.3.847

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*, 1030–1044. https://doi.org/10.1037/0096-1523.18.4.1030

Fortier-Gauthier, U., Dell'acqua, R., & Jolicœur, P. (2013). The "red-alert" effect in visual search: Evidence from human electrophysiology. *Psychophysiology*, *50*, 671–679. https://doi.org/10.1111/psyp.12050

Fukuda, K., & Vogel, E. K. (2011). Individual differences in recovery time from attentional capture. *Psychological Science*, *22*, 361–368. https://doi.org/10.1177/0956797611398493

Fukuda, K., Woodman, G. F., & Vogel, E. K. (2015). Individual differences in visual working memory capacity: Contributions of attention control to storage. In P. Jolicœur, C. Lefebvre, & J. Martinez-Trujillo (Eds.), *Attention and performance XXV: Mechanisms of sensory working memory* (pp. 105–119). London, UK: Academic Press. https://doi.org/10.1016/B978-0-12-801371-7.00009-0

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

Gaspelin, N., Ruthruff, E., & Lien, M.-C. (2016). The problem of latent attentional capture: Easy visual search conceals capture by task-irrelevant abrupt onsets. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 1104–1120. https://doi.org/10.1037/xhp0000214

Gottlieb, J. (2012). Attention, learning, and the value of information. *Neuron*, *76*, 281–295. https://doi.org/10.1016/j.neuron.2012.09.034

Gottlieb, J., Hayhoe, M., Hikosaka, O., & Rangel, A. (2014). Attention, reward, and information seeking. *Journal of Neuroscience*, *34*, 15497–15504. https://doi.org/10.1523/JNEUROSCI.3270-14.2014

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*, 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Hoffman, M. D., & Gelman, A. (2014). The no-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, *15*, 1593–1623.

Irons, J. L., & Leber, A. B. (2016). Choosing attentional control settings in a dynamically changing environment. *Attention, Perception & Psychophysics*, *78*, 2031–2048. https://doi.org/10.3758/s13414-016-1125-4

Irons, J. L., & Leber, A. B. (2018). Characterizing individual variation in the strategic use of attentional control. *Journal of Experimental Psychology: Human Perception and Performance*, *44*, 1637–1654. https://doi.org/10.1037/xhp0000560

JASP Team. (2018). JASP (Version 0.9) [Computer software]. Retrieved from https://jasp-stats.org/download/

Jost, K., Bryck, R. L., Vogel, E. K., & Mayr, U. (2011). Are old adults just like low working memory young adults? Filtering efficiency and age differences in visual working memory. *Cerebral Cortex*, *21*, 1147–1154. https://doi.org/10.1093/cercor/bhq185

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

Kim, M.-S., & Cave, K. R. (1999). Top-down and bottom-up attentional control: On the nature of interference from a salient distractor. *Perception & Psychophysics*, *61*, 1009–1023. https://doi.org/10.3758/BF03207609

Kristjánsson, Á., Jóhannesson, Ó. I., & Thornton, I. M. (2014). Common attentional constraints in visual foraging. *PLoS ONE*, *9*, e100752. https://doi.org/10.1371/journal.pone.0100752

Krummenacher, J., & Müller, H. J. (2012). Dynamic weighting of feature dimensions in visual search: Behavioral and psychophysiological evidence. *Frontiers in Psychology*, *3*, 221. https://doi.org/10.3389/fpsyg.2012.00221

Kruschke, J. K. (2013). Bayesian estimation supersedes the *t* test. *Journal of Experimental Psychology. General*, *142*, 573–603. https://doi.org/10.1037/a0029146

Kruschke, J. K., & Liddell, T. M. (2018). The Bayesian new statistics: Hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective. *Psychonomic Bulletin & Review*, *25*, 178–206. https://doi.org/10.3758/s13423-016-1221-4

Ly, A., Verhagen, J., & Wagenmakers, E.-J. (2016). Harold Jeffreys's default Bayes factor hypothesis tests: Explanation, extension, and application in psychology. *Journal of Mathematical Psychology*, *72*, 19–32. https://doi.org/10.1016/j.jmp.2015.06.004

Morse, W. H., & Skinner, B. F. (1957). A second type of superstition in the pigeon. *American Journal of Psychology*, *70*, 308–311. https://doi.org/10.2307/1419345

Mueller, S. T., & Piper, B. J. (2014). The Psychology Experiment Building Language (PEBL) and PEBL Test Battery. *Journal of Neuroscience Methods*, *222*, 250–259. https://doi.org/10.1016/j.jneumeth.2013.10.024

Müller, H. J., Heller, D., & Ziegler, J. (1995). Visual search for singleton feature targets within and across feature dimensions. *Perception & Psychophysics*, *57*, 1–17. https://doi.org/10.3758/BF03211845

Müller, H. J., Reimann, B., & Krummenacher, J. (2003). Visual search for singleton feature targets across dimensions: Stimulus- and expectancy-driven effects in dimensional weighting. *Journal of Experimental Psychology: Human Perception and Performance*, *29*, 1021–1035. https://doi.org/10.1037/0096-1523.29.5.1021

Robison, M. K., & Unsworth, N. (2017). Individual differences in working memory capacity predict learned control over attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *43*, 1912–1924. https://doi.org/10.1037/xhp0000419

Salvatier, J., Wiecki, T. V., & Fonnesbeck, C. (2016). Probabilistic programming in Python using PyMC3. *PeerJ Computer Science*, *2*, e55. https://doi.org/10.7717/peerj-cs.55

Sauter, M., Liesefeld, H. R., & Müller, H. J. (2019). Learning to suppress salient distractors in the target dimension: Region-based inhibition is persistent and transfers to distractors in a nontarget dimension. *Journal of Experimental Psychology: Learning, Memory, and Cognition.* Advance online publication. https://doi.org/10.1037/xlm0000691

Sauter, M., Liesefeld, H. R., Zehetleitner, M., & Müller, H. J. (2018). Region-based shielding of visual search from salient distractors: Target detection is impaired with same- but not different-dimension distractors. *Attention, Perception, & Psychophysics*, *80*, 622–642. https://doi.org/10.3758/s13414-017-1477-4

Sobel, K. V., & Cave, K. R. (2002). Roles of salience and strategy in conjunction search. *Journal of Experimental Psychology: Human Perception and Performance*, *28*, 1055–1070. https://doi.org/10.1037/0096-1523.28.5.1055

Sun, P., Chubb, C., Wright, C. E., & Sperling, G. (2016). Human attention filters for single colors. *Proceedings of the National Academy of Sciences*, *113*, E6712–E6720. https://doi.org/10.1073/pnas.1614062113

Theeuwes, J. (1992). Perceptual selectivity for color and form. *Perception & Psychophysics*, *51*, 599–606. https://doi.org/10.3758/BF03211656

Theeuwes, J. (2004). Top-down search strategies cannot override attentional capture. *Psychonomic Bulletin & Review*, *11*, 65–70. https://doi.org/10.3758/BF03206462

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

Theeuwes, J. (2013). Feature-based attention: It is all bottom-up priming. *Philosophical Transactions of the Royal Society: Series B*, *368*, 20130055. https://doi.org/10.1098/rstb.2013.0055

Theeuwes, J. (2018). Visual selection: Usually fast and automatic; seldom slow and volitional. *Journal of Cognition*, *1*, 29. 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. https://doi.org/10.1016/j.copsyc.2018.12.024

Theeuwes, J., Olivers, C. N. L., & Belopolsky, A. (2010). Stimulus-driven capture and contingent capture. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*, 872–881. https://doi.org/10.1002/wcs.83

Treisman, A. (1988). Features and objects: The Fourteenth Bartlett Memorial Lecture. *Quarterly Journal of Experimental Psychology*, *40A*, 201–237. https://doi.org/10.1080/02724988843000104

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

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

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

Wang, B., & Theeuwes, J. (2018c). Statistical regularities modulate attentional capture independent of search strategy. *Attention, Perception, & Psychophysics*, *80*, 1763–1774. https://doi.org/10.3758/s13414-018-1562-3

Watson, D. G., & Humphreys, G. W. (1997). Visual marking: Prioritizing selection for new objects by top-down attentional inhibition of old objects. *Psychological Review*, *104*, 90–122. https://doi.org/10.1037/0033-295X.104.1.90

Wichmann, F. A., & Hill, N. J. (2001). The psychometric function: I. Fitting, sampling, and goodness of fit. *Perception & Psychophysics*, *63*, 1293–1313. https://doi.org/10.3758/BF03194544

Wolfe, J. M. (2013). When is it time to move to the next raspberry bush? Foraging rules in human visual search. *Journal of Vision*, *13*, 10. https://doi.org/10.1167/13.3.10

Wolfe, J. M., Cain, M. S., & Aizenman, A. M. (2019). Guidance and selection history in hybrid foraging visual search. *Attention, Perception, & Psychophysics*, *81*, 637–653. https://doi.org/10.3758/s13414-018-01649-5

Woodworth, R. S., & Schlossberg, H. (1954). *Experimental psychology.* Oxford, UK: IBH.

Study V

Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies

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[10,220 words]

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Abstract

Victim Sensitivity (VS)—a personality trait reflecting the anxious expectation of being exploited by other people—predicts social distrust and uncooperativeness, but may also reflect a strong latent motivation to trust others. Therefore, information implying a violation of untrustworthiness expectations (i.e., trust-related attributes being associated with an untrustworthy-looking face) may be more motivationally relevant for victim-sensitive persons than information implying a violation of trustworthiness expectations (i.e., distrust-related attributes being associated with a trustworthy-looking face). To test this hypothesis, participants' (n=69) eye movements were recorded while they saw trustworthy or untrustworthy facial expressions and words that either confirmed or violated the expectation elicited by the respective face. Results show that victim sensitivity was associated with an attentional bias towards information violating untrustworthiness expectations, but not with an attentional bias towards information violating trustworthiness expectations. The study provides first evidence that victim sensitivity influences how trustworthiness-related social information is differentially processed.

[149 words]

Keywords: victim sensitivity, social information, untrustworthiness expectations, expectancy violation, attention allocation

Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies

People differ in the extent to which they fear being exploited: some hate the idea of falling prey to other people's selfish intentions, while others simply do not care. The personality trait that captures such a latent fear of exploitation has been referred to as "victim sensitivity". While previous research has mainly looked at the behavioral consequences of being dispositionally victim-sensitive, the question how exactly victim-sensitive people process social information related to trustworthiness or untrustworthiness, and, more importantly, how they process social information that *violates* their (un)trustworthiness expectancies[1], has been largely neglected so far. The present study aims to close this research gap.

According to the Sensitivity to Mean Intentions (SeMI) Model, victim-sensitive people expect others to be malevolent and selfish, and they are strongly motivated to avoid being exploited (Gollwitzer & Rothmund, 2009; Gollwitzer et al., 2013). As a consequence, individuals high in victim sensitivity are assumed to react more sensitively than persons low in victim sensitivity towards contextual cues that indicate untrustworthiness. In other words, the model proposes that victim-sensitive people become more easily suspicious, which ultimately makes them behave less cooperatively towards others.

A growing number of findings is in line with these assumptions (e.g., Fetchenhauer & Huang, 2004; Gollwitzer & Rothmund, 2011; Gollwitzer et al., 2005, 2009). For instance, victim-sensitive persons are less forgiving after transgressions in close relationships, reflecting a differential tendency to infer ulterior motives (Gerlach et al., 2012). In addition, people high in victim sensitivity behave uncooperatively even when confronted with only slight cues of untrustworthiness (Gollwitzer et al., 2009), and they rate neutral and angry looking faces to be less trustworthy compared to participants low in victim sensitivity (Gollwitzer et al., 2012; Study 1). This biased processing may explain why victim-sensitive people tend to underestimate other people's cooperativeness (Gollwitzer et al., 2012; Study 2). These and other findings (c.f. Maltese et al., 2016) suggest that victim sensitivity shapes information processing in a way that is personality-congruent (Rusting, 1998): victim-sensitive people are asymmetrically sensitive towards cues indicating selfishness and untrustworthiness, and they frequently adopt a "distrust mindset".

One of these cues is an interaction partner's facial expression: people swiftly draw inferences about a person's trustworthiness from their facial expression (Todorov et al., 2009; Willis & Todorov, 2006). However, the predictive validity of facial cues is far from perfect: even a grumpy-looking fellow can eventually turn out to be a nice person, and a truly selfish

[1] In this manuscript, the terms 'expectancy' and 'expectation' are used in an interchangeable way. However, 'expectation' is more frequently defined as a specific, verbalized construct, whereas 'expectancies' may be present without full awareness (i.e., implicit expectancies).

soul may be hidden under a nice and friendly appearance. So what if the judgment turns out to be wrong? How do victim-sensitive people process such expectancy violations?

Victim Sensitivity and Expectancy Violations

Assuming that victim-sensitive people are asymmetrically sensitive towards untrustworthiness (vs. trustworthiness) cues, it appears plausible to assume that victim-sensitive people also have a better memory for other people's untrustworthy (compared to trustworthy) behavior. However, previous research suggests an effect in the opposite direction. For instance, Süssenbach et al. (2016) showed that victim-sensitive individuals are particularly likely to remember information that *violates* their untrustworthiness expectations. In this study, participants saw pictures of male targets, and each target was accompanied by either a positive (i.e., trustworthiness-related, such as "scientist") or a negative (i.e., untrustworthiness-related, such as "trickster") social label. Approximately five seconds later, participants learned that the target had recently committed either a prosocial act (e.g., "rescued a kid that fell into a frozen pond") or an antisocial act (e.g., "stole valuable items from the apartments of older people"). Across trials, the act (prosocial vs. antisocial) was uncorrelated with the label (i.e., trustworthy vs. untrustworthy). In a subsequent surprise memory test, individuals high (vs. low) in victim sensitivity were more likely to correctly remember targets with a negative social label who committed a prosocial act—a *positive expectancy violation*—and less likely to correctly remember negatively labeled targets committing an antisocial act. Memory for *negative expectancy violations*, that is, positively labeled targets committing an antisocial act, did not differ between participants high vs. low in victim sensitivity. This suggests that victim-sensitive individuals are especially receptive towards positive expectancy violations, but not towards negative expectancy violations.

In a second study, Süssenbach et al. (2016) expanded these findings: in a first phase, participants saw targets accompanied by either a negative (untrustworthiness-related) or a positive (trustworthiness-related) label just as in Study 1; in a subsequent phase, they received additional information about whether the target had committed a prosocial or an antisocial act. The targets' trustworthiness was rated once after Phase 1 and a second time after Phase 2. Changes in trustworthiness ratings depended on participants' victim sensitivity: participants high (vs. low) in victim sensitivity updated their trustworthiness perceptions more strongly after positive expectancy violations (i.e., negatively labeled targets committing prosocial acts) than after negative expectancy violations (i.e., positively labeled targets committing antisocial acts). In sum, these two studies suggest that people high in victim sensitivity do not focus solely on untrustworthiness-related cues; instead, violations of untrustworthiness expectations seem to have an even bigger impact on memory and impression updating.

Motivational Relevance of Expectancy Violations

The finding that victim sensitivity predicts source memory for positive, but not for negative expectancy violations, is at odds with a number of other studies. Results from trust research, for example, indicate that humans identify and remember "cheaters"—people who violate social contracts—particularly well (e.g., Mealey et al., 1996; Oda, 1997). From an evolutionary perspective, it is indeed adaptive to pay more attention to potentially malevolent than to potentially benevolent interaction partners (Cosmides & Tooby, 1989). Hence, it seems surprising that victim-sensitive people show enhanced memory for prosocial behavior that violates untrustworthiness expectancies.

The solution for this apparent paradox may be deducted from an untested assumption of the SeMI Model (Gollwitzer & Rothmund, 2009; Gollwitzer et al., 2013). According to this model, victim sensitivity is rooted in (1) a *generalized expectation* that other people are untrustworthy and harbor mean intentions and, at the same time, (2) a *strong need* or motivation to trust others. Put differently, while victim-sensitive people expect others to be untrustworthy, they would love to live in a world in which other people can be trusted. Information contradicting their negative expectations about other people thus resonates with their strong need to trust; this type of expectancy violation is more *motivationally relevant* for victim-sensitive than for victim-insensitive people.

Importantly, Süssenbach et al. (2016) have focused only on source memory (Study 1) and impression updating (Study 2), but they never looked at earlier stages of information processing, such as attention allocation. Notably, attention allocation is influenced to a large extent by the motivational relevance ascribed to a stimulus (e.g., Summerfield & Egner, 2009). Therefore, a strict test of the assumption that positive expectancy violations are particularly motivationally relevant for victim-sensitive individuals would be to show that victim sensitivity predicts attention allocation to these positive expectancy violations. We will test this hypothesis in the present study.

Attention Allocation to Motivationally Relevant Stimuli

Our assumption that the motivational relevance of a stimulus predicts attention allocation to it and, thus, causes a better source memory for it, is in line with a large number of findings in the literature. Due to limited processing capacities of the human brain, only a subset of the available visual information can be processed in detail, and, therefore, attentional filters are needed to select and prioritize those stimuli that are most relevant for the organism's goals and needs (e.g., Lavie & Dalton, 2014). This process is referred to as selective visual attention.

Notably, selective visual attention determines to a great extent which information is processed and encoded into long-term memory (Chun et al., 2011; Chun & Turk-Browne, 2007). Attentional processing, on the other hand, is influenced by past experiences and (implicitly) acquired knowledge as well: extracted regularities from the visual environment, which are stored in memory, can be used for guiding visual search and the selection of stimuli, a process which is referred to as statistical learning (e.g., Bergmann et al., 2019; Goujon et al., 2015; Theeuwes, 2018). This interdependence between memory and visual attention makes it likely that a source memory advantage for positive expectancy violations (as in Süssenbach et al., 2016) is preceded by attention allocation towards these violations (for more studies investigating the relationship between attention and memory, see Aly & Turk-Browne, 2016; Cabeza et al., 2008; Heuer & Schubö, 2018; Wolfe et al., 2007).

Even more importantly, selective visual attention is influenced by motivation and motivational significance (e.g., Brosch & Van Bavel, 2012; Dietze & Knowles, 2016; Feldmann-Wüstefeld et al., 2016; Lang et al., 1997; Summerfield & Egner, 2009), and expectation violations constitute a particularly salient class of motivational stimuli (Proulx et al., 2017). However, motivational relevance does not seem to be a static or invariant construct; instead, the significance of stimuli is highly context dependent and reflects the flexible motivational state of the perceiver (Brosch & Van Bavel, 2012). For instance, DeWall et al. (2009) induced a specific motivational state by thwarting participants' need for social belonging. As a consequence, visual attention was preferentially allocated to desired, goal-relevant stimuli, that is, to cues signaling social acceptance and affiliation. Thus, whenever needs or goals are threatened, attention is allocated to information that resonates with the respective need or to possibilities for satisfying the thwarted need. In addition, individual differences in the strength or accessibility of needs and motivational concerns influence the relevance ascribed to cues or information and affect the amount of attentional capture as well (Brosch & Van Bavel, 2012).

The Present Study

Based on our theorizing and the findings reviewed here, we expect to find a similar bias for positive expectancy violations in the allocation of visual attention in victim-sensitive individuals. As argued in the SeMI model (Gollwitzer & Rothmund, 2009; Gollwitzer et al., 2013), victim-sensitive persons (in contrast to victim-insensitive persons) are characterized by a particularly strong need to trust others. Thus, whenever a social cue elicits an untrustworthiness expectation (e.g., a grumpy face), information that is inconsistent with this cue (e.g., a positive social attribute) becomes particularly motivationally relevant for victim-sensitive individuals. More specifically, we argue that victim sensitivity predicts attention allocation to stimuli suggesting a violation of untrustworthiness expectations (i.e., positive expectancy violations).

With regard to negative expectancy violations, our predictions are less straightforward. Based on our reasoning and previous findings (e.g., Süssenbach et al., 2016), victim sensitivity should predict preferential attention allocation only towards positive expectancy violations, but not towards negative expectancy violations. However, past research has also shown that victim-sensitive persons focus more strongly on information signaling untrustworthiness when evaluating other people's behavior and intentions than victim-insensitive persons (Gollwitzer et al., 2012). Put differently: due to their latent fear of exploitation, people high in victim sensitivity are particularly attracted to cues associated with untrustworthiness and selfishness. Therefore, one could argue that victim sensitivity also predicts attention allocation towards information indicating that a person is not as trustworthy as one would expect.

To test these hypotheses, an eye tracking study was conducted because saccadic eye movements are tightly interlinked with attentional selection processes; thus, they are well suited as proxies for attentional processes (Chun et al., 2011; Deubel & Schneider, 1996). Participants were seated in front of a computer screen and an eye tracker that recorded saccades and fixations. On this screen, pictures of male faces with positive (i.e., trustworthy) or negative (i.e., untrustworthy) facial expressions appeared and, after a short time interval, the faces were complemented by words related to trustworthiness or untrustworthiness. Matches and mismatches between the words and the respective facial expressions were used to operationalize confirmations and violations of (un)trustworthiness expectations, respectively, and to compare the allocation of attention (measured by the eye movement pattern) towards these different kinds of stimuli as a function of victim sensitivity.

Method

Open Data

In accordance with open science principles, primary data from this project can be downloaded from the Open Science Framework [the data are available to reviewers upon request and will be uploaded on OSF once the paper is accepted].

Power Analysis

We determined sample size by calculating an a priori power analysis using G*Power 3.0.8 (Faul et al., 2007). Based on pilot study data, medium-sized correlations between victim sensitivity and eye tracking parameters seemed realistic; therefore we used an effect size estimate of $\rho=.30$, with an alpha of .05 (one-tailed) and power of 0.8. The recommended minimum sample size given these parameters was 67.

Participants

A total of 70 undergraduate students from a German university were recruited via email advertisement and participated in the study for partial course credit or financial compensation. The dataset of one participant had to be excluded due to a lack of knowledge of the German language; therefore, the final analysis sample consisted of 69 students (52 female, 17 male). All participants had normal or corrected-to-normal vision and were between 18 and 32 years old (M_{age}=21.9, *SD*=2.78).

Apparatus

The experiment was conducted in a dimly lit and sound-attenuated room. The participants were seated in front of a 32-inch monitor (1920 × 1080 pixels, 120 Hz) and placed their heads on a chinrest, so that their eyes were aligned with the center of the screen in a distance of 100 cm. We recorded eye movements of the participants' right eye with an EyeLink 1000 Plus eye tracker (SR Research Ltd.), recording with 1000 Hz and calibrated with the 13-point calibration procedure. E-Prime Professional 2 (Psychology Software Tools) was used for stimulus presentation and response collection.

Materials

We selected 120 computer-generated pictures of frontal male faces from two databases freely available to researchers who conduct non-profit, academic research (Original Computer Generated Faces; see Oosterhof & Todorov, 2008). All of these 120 pictures depicted bald, Caucasian males whose facial appearance differed in the level of trustworthiness. Specifically, we used 45 faces with trustworthy facial expressions and 45 faces with untrustworthy facial expressions to induce expectations of trustworthiness and untrustworthiness, respectively. In addition, we selected 30 faces with neutral facial expressions for practice trials. All faces were generated using FaceGen Modeller Version 3.1 and 3.2 (Singular Inversions, 2005, 2007) according to the trustworthiness computer model developed by Oosterhof and Todorov (2008). Examples for each of the three face categories can be found in Figure 1.

FIGURE 1

Examples of Face Stimuli

Note. Examples of untrustworthy (left), neutral (middle), and trustworthy (right) faces.

Furthermore, a total of 198 German nouns and adjectives that we thought suitable to describe person characteristics were selected from two freely accessible databases: the Berlin Affective Word List Reloaded (BAWL-R; Võ et al., 2009) and the Age-Dependent Evaluations of German Adjectives database (AGE; Grühn & Smith, 2008a, 2008b). In a second step, 136 undergraduate students (M_{age}=23.9, *SD*=9.72, 77% female) rated the trustworthiness of each of the 198 words on a scale from 1 [very strongly associated with untrustworthiness] to 7 [very strongly associated with trustworthiness]. Based on the ratings of this norming study, we selected 20 trustworthy words with a mean trustworthiness of 5.66 (*SD*=0.33), 20 untrustworthy words with a mean trustworthiness of 1.71 (*SD*=0.30), and 80 neutral words (*M*=4.08, *SD*=0.51) as final stimulus material. Words associated with trustworthiness were for example "honest" or "just", words associated with untrustworthiness were for example "greedy" and "selfish", and neutral words were for example "smoker" and "popular". In a final step, these 120 words were sorted into 30 combinations consisting of four words each. Combinations always entailed one trustworthy and three neutral words (trustworthy word condition; *n*=10), one untrustworthy and three neutral words (untrustworthy word condition; *n*=10) or one trustworthy, one untrustworthy, and two neutral words (competition condition; *n*=10). Importantly, words within one combination were matched with regard to word length (i.e., number of letters) and word frequency (i.e., frequency of appearance per million words); these features have been shown to influence word processing (e.g., Võ et al., 2009).[2] In addition, each individual word appeared only in one combination and all words were capitalized for standardization purposes.

Design

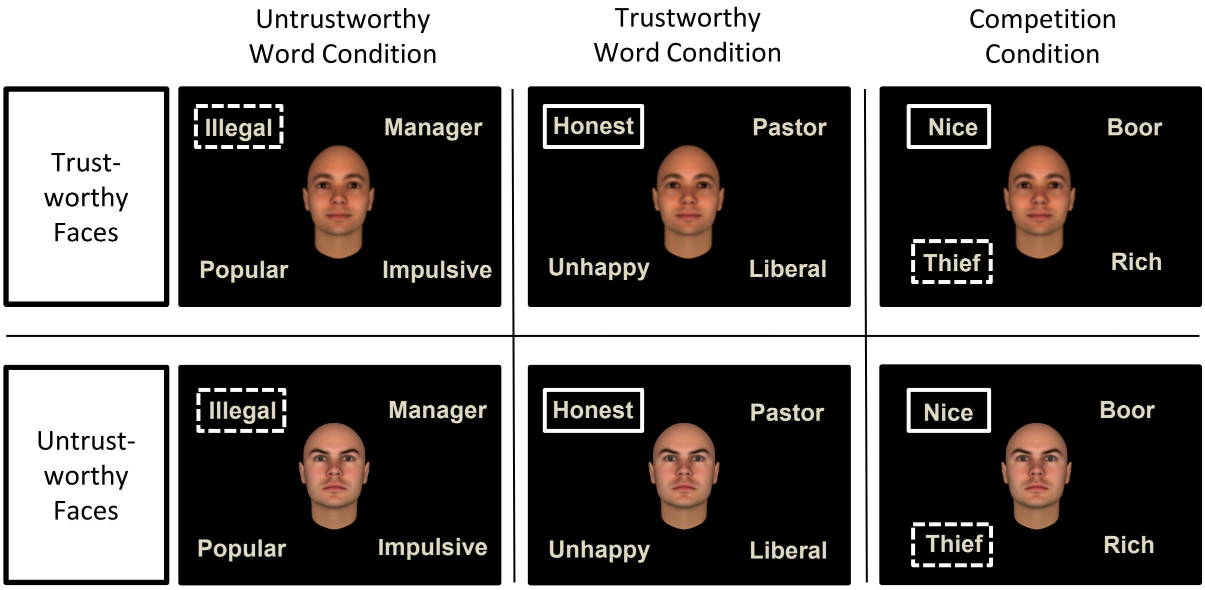
We used a within-subjects design with face condition (trustworthy vs. untrustworthy face) and word condition (trustworthy word vs. untrustworthy word vs. competition condition) as factors, resulting in six experimental conditions (see Figure 2). Each trial consisted of the presentation of a face together with one randomly chosen word combination. Therefore, trials constituted either a match between word condition and face condition (e.g., untrustworthy word and untrustworthy face), a mismatch between word condition and face condition (e.g., untrustworthy word and trustworthy face), or both (e.g., competition condition and trustworthy face).[3]

[2] We also planned to match the words with regard to word valence and arousal. However, this turned out to be difficult because trustworthiness, valence, and arousal ratings were highly correlated (r = .57–.82). Not entirely surprising, we found untrustworthy words to be more negative and more arousing than words with neutral trustworthiness ratings, while trustworthy words were more positive and less arousing. As a consequence, words within one combination differed not only in trustworthiness levels but also in valence and arousal.

[3] However, results in the two competition conditions were inconsistent and will thus not be referred to further (see Appendix A for an overview of the results). The lack of findings in these conditions may be due to the fact that conflicting information is given (a face is always presented with a trustworthy and an untrustworthy word simultaneously, which might have cancelled each other out).

FIGURE 2

Experimental Conditions



Note. Either a trustworthy (first line) or an untrustworthy face (second line) was presented at screen center. The face was complemented by either one untrustworthy and three neutral words (left column), one trustworthy and three neutral words (middle column), or one trustworthy, one untrustworthy, and two neutral words (right column). In this figure, trustworthy and untrustworthy words are highlighted by solid and dashed boxes, respectively, but these markings were not shown in the experiment.

In total, the experiment consisted of 300 trials that were organized in 10 blocks with 30 trials each. Importantly, only trustworthy *or* untrustworthy faces were used in each block, resulting in 50% untrustworthy and 50% trustworthy face blocks. The order in which these blocks were presented was counterbalanced across participants. In addition, each block contained all 30 word combinations and 30 different faces in a random order, but combinations and faces were used repeatedly across blocks.

Procedure

The design and methods of this study were approved by a local ethics committee. Participants were tested individually in a session that took about 1.5 hours and gave informed consent before the experiment began. On arrival, visual acuity was assessed using an Oculus Binoptometer 3 (a visual acuity of 0.8 was required for participation), and impairments in stereo vision and color vision were ruled out. Participants were then informed that the study consisted of a computer-based eye tracking experiment that was ostensibly designed to investigate “the relation between eye movements and memory in the context of different feature configurations”. We used this cover story to disguise the actual purpose of the study and also implemented a memory task to make it more plausible. For this reason, the students were told that they would see faces together with words, and that after every fifth trial, a recognition test would take place. In this recognition test, participants had to categorize a word as either “old” (i.e., contained within the last five trials) or “new”, and feedback on task performance was given at regular intervals.[4]

At the beginning of the experiment, participants were seated in front of the computer screen. After calibration of the eye tracker, participants were first familiarized with the task in a practice block consisting of 30 trials[5], followed by 10 experimental blocks. Between blocks, participants were informed about their recognition accuracy in the “memory task” and had the opportunity to take short breaks before the experiment was continued. Within experimental blocks, each trial started with a fixation dot surrounded by a thin line presented at screen center. After participants successfully fixated this dot, the trial started and the thin line disappeared. After 500 milliseconds (ms), a picture of a male face with a trustworthy or untrustworthy facial expression replaced the fixation dot and was presented for 2000 ms, before four words complemented the face for another 3000 ms. Each word was presented in one quadrant of the display, so that every word had the same distance to the face at screen center. The assignment of the four words of each combination to the four quadrants was randomized for every trial. In addition, the font size of the words was adjusted (Arial 36, bold) so that the words were peripherally recognizable—at least to some extent—when the face at screen center was fixated. After the presentation of the face and the words, a blank screen appeared for 500 ms, before the next trial started (see Figure 3 for a schematic overview of the trial procedure).

After the main experiment, participants took part in two additional tasks that we included for exploratory purposes: first, 30 additional trials were implemented that also consisted of the presentation of a face and four words like in the main experiment.[6] This time, however, participants were instructed to rate the likeability of each face on a scale from 1 [very dislikeable] to 7 [very likeable]. Furthermore, a nonverbal working memory test (PEBL Corsi block-tapping task; Mueller & Piper, 2014) was conducted.

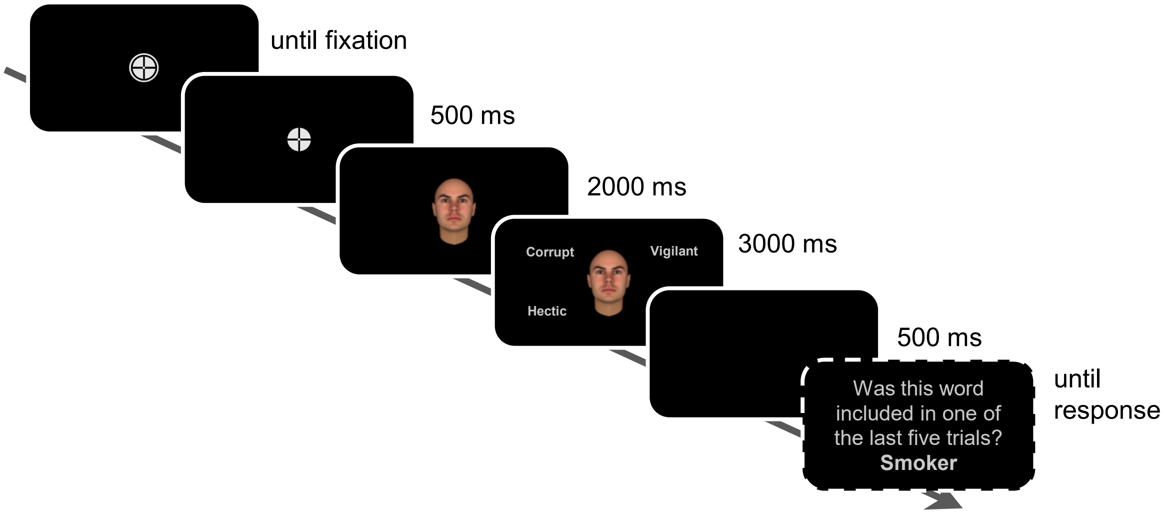
Finally, participants were probed for suspicion and answered a short follow-up survey about the experimental tasks and the strategies they applied during the tasks. Next, victim sensitivity was assessed with ten items from the Justice Sensitivity Inventory (Cronbach’s α=.84; Schmitt et al., 2010), that were rated on a six-point Likert scale from 0 [not at all true] to 5 [absolutely true]. Example items are “I ruminate for a long time when other people are treated better than me”, and “It makes me angry when others receive a reward that I have earned”. In addition, we assessed four personality scales as possible covariates, namely general

[4] We included this memory task not only to distract participants from the actual purpose of the study but also to make sure that the presented words were read and processed in a comparable manner. However, participants’ recognition accuracy was of no further interest.
[5] Practice trials were identical to the subsequent experimental trials but only contained faces with neutral facial expressions and words with neutral trustworthiness ratings not used in the main experiment.
[6] For this additional block, we used the same word combinations as before but selected fifteen new trustworthy and fifteen new untrustworthy faces from our pool of male faces.

trust (with a German version of the General Trust Scale by Yamagishi & Yamagishi, 1994), neuroticism (BFI-10; Rammstedt & John, 2007) and the other three facets of justice sensitivity (observer, beneficiary, and perpetrator sensitivity; Schmitt et al., 2010). Finally, participants were thanked for their participation and fully debriefed.

FIGURE 3

Schematic Overview of one Experimental Trial.



Dependent Variables

We used the software EyeLink Data Viewer (SR Research Ltd.) to pre-process the eye tracking data and IBM SPSS Statistics Version 25 for subsequent statistical analyses. The main outcome variables in this study were different eye tracking parameters that we calculated separately for each of the four words in each trial. Neutral words, however, were not part of our hypotheses and will thus not be referred to any further.

Attention allocation was operationalized via several eye tracking parameters (see Holmqvist et al., 2011; Süssenbach et al., 2012). More specifically, we measured (1) how long participants fixated the word when first landing on it ("first fixation duration"), (2) how long the word was fixated in total ("dwell time"), and (3) how often participants fixated the respective word per trial ("fixation count"). In addition, we also measured (4) which word was fixated first in each trial ("destination of the first saccade"). These dependent variables represent slightly different "stages" of attention and visual information processing and reflect earlier/faster (destination of the first saccade, first fixation duration) as well as later/slower (dwell time, fixation count) cognitive processes (see Holmqvist et al., 2011). In reading research, for example, the duration of the first fixation is often defined as a measure of identification or (lexical) processing time, while dwell time—i.e., the total amount of time spent fixating on a word—is sought to reflect higher integrational and evaluative processes as well (Holmqvist et al., 2011; Inhoff & Radach, 1998; Rayner, 1998). Therefore, effects of violations and confirmations of (un)trustworthiness expectations may differ between these four dependent variables (Inhoff & Radach, 1998).

Results

We excluded trials from analyses in which no word was fixated, which applied to 32 trials (0.001%) in total. Mean values on each of the four dependent variables described above are shown in Table 1, broken down by experimental condition. To compare attention allocation between words, we calculated "attentional bias scores" for each dependent variable for trustworthy and untrustworthy faces. These bias scores—or difference scores—were calculated across trustworthy and untrustworthy word conditions. More specifically, mean scores for face-congruent words were subtracted from mean scores for face-incongruent words. Thus, positive scores indicate preferential attention towards face-incongruent words relative to face-congruent words, while negative scores reflect an attentional bias away from face-incongruent words. Because bias scores were calculated separately for each of the four dependent variables described above (first fixation duration, dwell time, fixation count, destination of the first saccade), broken down by face types (untrustworthy vs. trustworthy faces), this procedure resulted in 8 attentional bias scores in total.

To test our hypotheses, bivariate correlations between attentional bias scores and victim sensitivity were probed for significance (see below). Although we will focus mainly on these correlations in the following results sections, we also used multilevel modeling (i.e., mixed models) to analyze the data with regard to first fixation duration, dwell time, and fixation count. Here, random intercepts were modeled to account for the nested data structure. More specifically, two fixed level-1 predictors were included for face type (untrustworthy = -0.5, trustworthy = +0.5) and word type (untrustworthy = -0.5, trustworthy = +0.5), respectively. At level 2, victim sensitivity (z-standardized) as well as the respective interaction terms were entered. Three-way interaction effects between face type, word type, and victim sensitivity were probed for significance. Results of these analyses are reported in the subsequent footnotes. Detailed results are reported in Appendix B.

Attentional Biases in the Trustworthy and Untrustworthy Word Conditions

Overall, attentional biases were only observed in some, but not in all dependent variables (see Table 1). For untrustworthy faces, we found significant positive difference scores for fixation count ($t(68)=5.275$, $p < .001$, $d=0.63$, 95% CI [0.37, 0.89]) and dwell time ($t(68)=4.668$,

TABLE 1

Means and Standard Deviations of Eye Movement Variables for Relevant Words Trustworthy and Untrustworthy Word Conditions

Word	First fixation duration [ms]	Dwell time [ms]	Fixation count	Destination of the first saccade [%]
U face				
U word	265 (45)	472[a] (70)	1.98[a] (0.33)	24.75 (6.25)
T word	261 (47)	493[a] (79)	2.10[a] (0.41)	24.61 (6.15)
T face				
U word	264 (45)	477 (71)	1.99[a] (0.36)	24.35 (6.09)
T word	260 (48)	487 (78)	2.07[a] (0.39)	25.48 (6.12)

Note. U face = untrustworthy face, T face = trustworthy face, U word = untrustworthy word, T word = trustworthy word. Values reported for “destination of the first saccade” represent the percentage of trials in which the word was fixated first. Standard deviations are shown in parentheses.

[a] Significant difference between trustworthy and untrustworthy words in one face condition ($p < .001$, two-tailed).

TABLE 2

Correlations of Attentional Bias Scores with Victim Sensitivity Trustworthy and Untrustworthy Word Conditions

Bias score	VS	*p*	95% CI	
			LL	*UL*
U face				
First fixation duration	.23[+]	.055	−.007	.443
Dwell time	.09	.466	−.150	.320
Fixation count	−.25*	.037	−.459	−.014
Destination of the first saccade	−.06	.600	−.293	.179
T face				
First fixation duration	.02	.846	−.218	.255
Dwell time	.27*	.025	.036	.476
Fixation count	.26*	.032	.025	.468
Destination of the first saccade	.15	.228	−.090	.373

Note. U face = untrustworthy face, T face = trustworthy face; VS = victim sensitivity; 95% CI = 95% confidence interval, *LL* = lower limit, *UL* = upper limit.

[*] Significant correlation ($p < .05$, two-tailed).

[+] Significant correlation ($p < .05$, one-tailed).

$p < .001$, d=0.56, 95% CI [0.31, 0.81]), illustrating that after the presentation of untrustworthy faces, face-incongruent trustworthy words were fixated more often and for a longer time than face-congruent untrustworthy words. In the trustworthy face condition, however, a negative bias score was visible with regard to fixation count ($t(68) = -4.183$, $p < .001$, $d = -0.51$, 95% CI [−0.76, −0.25]): trustworthy words—although confirming the facial expression—were again fixated more often than untrustworthy words. Thus, these "main effects" speak for an attentional bias towards positive, trustworthiness-related words in general.[7]

Hypothesis Tests: Correlations with Victim Sensitivity

To test the assumption that victim sensitivity predicts attention allocation towards expectancy violations, we correlated attentional bias scores with victim sensitivity in a second step. These correlations are reported in Table 2. In addition, a graphical representation of predicted means (from the multilevel analyses) in first fixation duration, dwell time, and fixation count—as a function of victim sensitivity, face type, and word type—is shown in Figure 4.

First Fixation Duration

In line with our hypothesis, we found a positive correlation between victim sensitivity and the attentional bias score for first fixation durations in the context of untrustworthy faces ($r(67)$=.23, p=.06, two-tailed, 95% CI [−0.01, 0.44][8]). Thus, victim sensitivity predicted longer initial fixations on face-incongruent trustworthy words than on face-congruent untrustworthy words after untrustworthy faces had been presented. In contrast, we did not find a significant correlation in the context of trustworthy faces ($r(67)$=.02, p=.85, two-tailed, 95% CI [−0.22, 0.26]), implying that victim sensitivity did not predict longer first fixations on face-incongruent words in the context of trustworthy faces. In other words, no attentional bias was found for negative expectancy violations.[9]

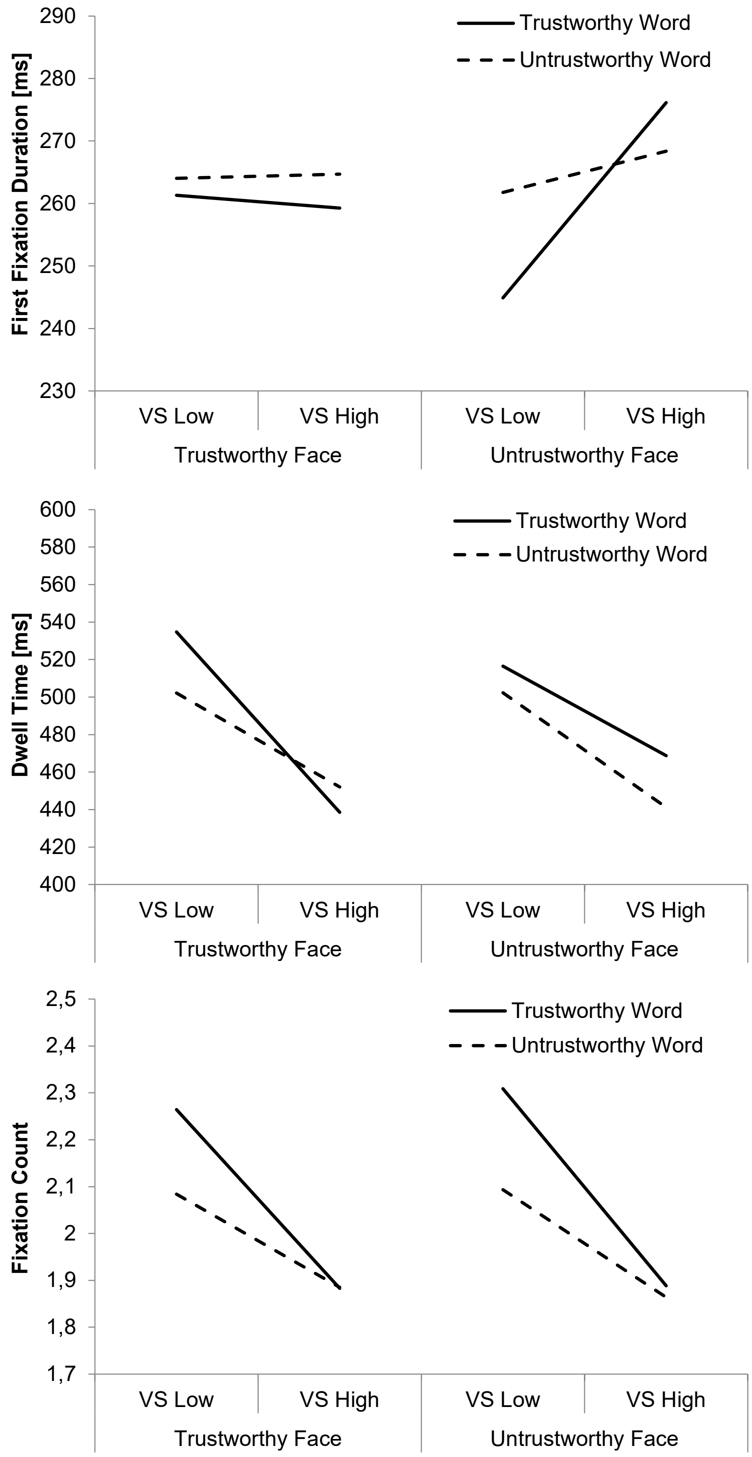
Dwell Time

In contrast to first fixation duration, victim sensitivity was uncorrelated ($p = .47$) with dwell time differences in the context of untrustworthy faces. Therefore, victim sensitivity did not predict longer dwell times on face-incongruent (vs. face-congruent) words in this facial

[7] In the multilevel analyses, we found a significant main effect of word type ($p_s < .001$), while the main effect of face type and the face type x word type interactions did not reach significance ($p_s > .10$). These results thus confirm that—across face conditions—trustworthy words were fixated more often and for a longer time than untrustworthy words.
[8] Note: in the context of correlation analyses, p-values < .10 are interpreted as significant when hypotheses are directional and one-tailed testing is therefore warranted.
[9] In our multilevel analysis, the three-way interaction between victim sensitivity, face type, and word type did not reach significance ($p = .15$). However, in separate analyses for the two face conditions, the expected victim sensitivity x word type interaction was marginally significant for untrustworthy faces ($p = .075$), while no such interaction was found for trustworthy faces ($p = .83$).

FIGURE 4

Visualization of Attentional Biases



Note. Predicted means in first fixation duration, dwell time, and fixation count (obtained from the multilevel analyses) visualizing the face type × word type interaction effects for participants low vs. high in victim sensitivity (±2 *SD* from the sample mean).

context. However, we did observe a significant positive correlation between victim sensitivity and dwell time differences in the context of trustworthy faces ($r(67)=.27$, $p=.03$, two-tailed, 95% CI [0.04, 0.48]), suggesting that participants high (vs. low) in victim sensitivity spent more time fixating face-incongruent untrustworthy words compared to face-congruent trustworthy words.[10] However, as Figure 4 shows, this effect was mainly driven by a strong negative correlation between victim sensitivity and dwell times on trustworthy words. Put differently: while people low in victim sensitivity allocated preferential attention toward face-congruent trustworthy words in the context of trustworthy faces, this consistency or positivity effect disappeared (and was even reversed) with increasing victim sensitivity.

Fixation Count

Victim sensitivity was correlated with the attentional bias score for fixation count both in the context of untrustworthy faces ($r(67)= -.25$, $p=.04$, two-tailed, 95% CI [−0.46, −0.01]) as well as in the context of trustworthy faces ($r(67)=.26$, $p=.03$, two-tailed, 95% CI [0.03, 0.47]). Contrary to our hypothesis, the negative correlation for untrustworthy faces implied *fewer* fixations on (face-incongruent) trustworthy words for people high (vs. low) in victim sensitivity, that is, an attentional bias away from positive expectancy violations. However, the positive correlation in the context of trustworthy faces shows that higher victim sensitivity was also associated with fewer fixations on trustworthy words after trustworthy faces had been presented.[11] In other words, trustworthy words were always fixated more often than untrustworthy words when victim sensitivity was low, but this “positivity bias” (which corresponds to the main effect of word type found for fixation count) disappeared with increasing victim sensitivity. Thus, whereas *victim-insensitive* participants were more inclined to fixate on trustworthy words than on untrustworthy words (irrespective of whether these words were presented after a trustworthy or an untrustworthy face), *victim-sensitive* individuals tended to fixate equally often on both word types in both facial contexts. Therefore, these effects seem to reflect attention allocation towards (or away from) specific word content rather than reactions to expectancy violation vs. confirmation.

Destination of the first Saccade

Bias scores in this dependent variable were uncorrelated with victim sensitivity in both face conditions (all $p_s > .23$). In sum, our findings show that victim sensitivity (VS) is associated with preferential attention towards positive expectancy violations. Participants high (vs. low)

[10] The results of the multilevel analysis confirm these findings. In accordance with the correlational analyses, we found a significant victim sensitivity x face type x word type three-way interaction effect ($p = .04$). Following up on this significant interaction, separate analyses for each face condition demonstrated a significant interaction between VS and word type only for trustworthy faces ($p = .02$), but not for untrustworthy faces ($p = .50$).

[11] Accordingly, the results of the multilevel analysis showed a significant victim sensitivity x word type interaction across face types ($p = .002$), while the VS x word type x face type three-way interaction was not significant ($p = .95$).

in VS showed longer initial fixations on trustworthy words than on untrustworthy words after untrustworthy faces had been presented. However, participants high in VS also showed a general tendency to fixate trustworthy words less often, independent of the facial context. This pattern of results was somewhat unexpected but (1) it seemed to reflect an attentional bias to specific word content rather than to expectancy violations (because the effect appeared in both face conditions), and (2) it may be explained by the fact that trial durations were held constant in our study. More specifically, we hypothesized that because word presentation was limited to 3000 ms, the number of fixations might be negatively related to first fixation durations (c.f. Holmqvist et al., 2011). Indeed, exploratory correlation analyses revealed a negative relation between the bias scores in first fixation duration and fixation count ($r(67) = -.36$, $p = .002$, two-tailed, 95% CI [−0.55, −0.14]). This finding implies that when the initial fixation on the face-incongruent word (relative to the face-congruent word) was longer, fewer fixations were credited to this word (relative to the face-congruent word) in total—presumably because a longer initial fixation might have allowed for a more profound processing already.

In contrast to positive expectancy violations, our results indicate that VS was not associated with an attentional bias towards negative expectancy violations. Although we did find significant correlations of VS with dwell time and fixation count differences in the context of trustworthy faces, these seemed to be mainly driven by a positivity bias associated with low VS, which disappeared with increasing VS (cf. Figure 4). Thus, whereas victim-insensitive participants showed longer dwell times and more fixations on trustworthy words than on untrustworthy words in this facial context, victim-sensitive individuals fixated about equally long (and equally often) on both word types.

Discussion

In the present research, we examined how victim-sensitive individuals process social information related to trustworthiness or untrustworthiness, and, more specifically, how they process positive and negative expectancy violations in this context. In line with our primary hypothesis, victim sensitivity (VS) predicted attention allocation towards positive expectancy violations: after the presentation of untrustworthy faces, victim-sensitive individuals (but not victim-insensitive individuals) tended to fixate face-incongruent trustworthy words longer than face-congruent untrustworthy words when first landing on it, which suggests a deeper processing of cues that positively violate negative initial expectations (Holmqvist et al., 2011). This result corroborates our assumption that violations of untrustworthiness expectations are especially motivationally relevant for victim-sensitive persons (because of their strong need to trust, c.f. Gollwitzer et al., 2013), and therefore receive preferential attention. In addition, this result is in line with previous findings showing that people high (vs. low) in VS are more likely to (a) remember information suggesting that an initially untrustworthy target person may not be so untrustworthy after all, and (b) update their expectations more readily in such cases of positive expectation violations (Süssenbach et al., 2016). Possibly, these findings can be explained by the effects observed in the present study: victim-sensitive people preferentially attend to stimuli violating their negative expectations; and therefore, these stimuli are stored in memory (Chun et al., 2011; Chun & Turk-Browne, 2007).

Notably, VS not only predicted longer first fixations on positive expectancy violations, but also *fewer* fixations on these words. At first glance, the reduced number of fixations seems to contradict the notion that, for victim-sensitive individuals, violations of untrustworthiness expectations are rather attended than confirmations of such expectations. However, high VS was associated with fewer fixations on trustworthy words in both facial contexts (i.e., while victim-insensitive individuals fixated more on trustworthy than on untrustworthy words in both face conditions, victim-sensitive participants did show no such "positivity bias"). Therefore, differences in this dependent variable seem to reflect attention allocation towards (or away from) specific word content, independent of any expectations the participants might have held.

Moreover, characteristics of the "memory task" that we used in our study may have contributed to the lower fixation count for positive expectancy violations. As mentioned above, we included this task for two reasons: (1) to increase the credibility of the cover story and (2) to ensure that participants would read and semantically process the words presented in each trial. As part of this task, a recognition test was implemented after every fifth trial, in which participants were asked to identify a presented word as "old" (i.e., contained in one of the last five trials) or "new". Thus, participants were motivated to fixate each of the four words in each trial at least once to successfully memorize them. In addition, the task was associated with time pressure, as the words were presented for only 3000 ms in total. Therefore, the memory task might have contributed to the lower number of fixations on expectancy-violating trustworthy words: probably, victim-sensitive persons showed fewer fixations on these words (relative to expectancy-confirming untrustworthy words), because they were sufficiently processed during the prolonged first fixation and because the memory task demanded to attend the other words as well. Previous research confirms an inverse relationship between number of fixations and fixation durations when trial durations are held constant (Holmqvist et al., 2011), and the difference scores of fixation count and first fixation duration were negatively correlated in our study as well.

Importantly, although the memory task might have affected our results in some ways, it should be noted that its implementation resulted in a more *conservative* testing of our hypothesis. Because of this task, participants were not motivated to focus their attention on one word but to try to attend to *all* words. As a consequence, differences in attention allocation between face-congruent and face-incongruent words should be small, and therefore harder to detect. As both nature and difficulty of the task at hand have been shown to influence cognitive processes and eye movements (Rayner 1998, 2009), other experimental tasks and instructions—such as free reading or search tasks—would probably result in different viewing patterns. Future studies should hence compare attention allocation under different instructions to see whether our findings generalize to other experimental tasks and settings.

Characteristics of the materials and instructions used in our study might also be responsible for the lack of effects on the "destination of the first saccade", which can be seen as an indicator of early attention capture. Contrary to our hypothesis, results showed that expectancy-violating words were not fixated earlier in the trial than expectancy-confirming words, irrespective of face or word condition or VS. One plausible reason for this null result might be the tendency of most participants to scan all the words presented on the screen in the order in which they are usually processed (i.e., from the upper left to the lower right side in Latin script). These habits might have overshadowed any "destination of the first saccade" effects. Furthermore, it is also possible that expectancy-violating words did not grab attention because participants were not able to adequately process the words in parafoveal vision when fixating on the face at screen center (although we made sure to use an appropriate font size). Future research should therefore consider using pictorial material to avoid these difficulties.

Negative Expectancy Violations

In accordance with the findings reported by Süssenbach et al. (2016), VS was not associated with preferential attention towards *negative expectancy violations* in our study. Notably, we did find significant correlations between VS and the difference scores in dwell time and fixation count in the context of trustworthy faces. However, effects in fixation count were—as already described—not limited to one face type and therefore presumably represent effects of specific word content rather than effects of expectancy violations. In addition, visualizations of the relationships implied that the correlations were mainly driven by victim-insensitive individuals' preferential attention for trustworthy words (i.e., words confirming the positive expectation). Put differently: while victim-insensitive individuals showed both longer dwell times and a larger number of fixations on expectation-confirming trustworthy words than on expectation-violating untrustworthy words, victim-sensitive people attended both word types about equally long and often. Thus, low VS was related to a positivity bias that disappeared with increasing victim sensitivity, but high VS was not associated with an attentional bias toward negative expectancy violations.

Limitations

In the present study, we used a newly developed paradigm to provide first evidence for the assumption that victim sensitivity predicts attention allocation towards information that violates untrustworthiness expectations. However, in addition to the strengths of the study there are also some limitations to consider.

First, the words used in the present experiment—although matched on important dimensions like word length and word frequency—differed not only with regard to trustworthiness, but also with regard to valence and arousal. In fact, ratings on these three dimensions showed high intercorrelations, and while untrustworthy words were found to be negative and highly arousing, trustworthy words tended to be positive and less arousing. In addition, the same applied to the facial stimuli that we selected. As can be seen in Figure 1, the faces that we used to induce trustworthiness expectations resemble friendly-looking, smiling faces that signal happiness. The untrustworthy faces, on the other hand, have narrowed eyes and look much more "grumpy", which results in a more aggressive or hostile appearance. Therefore, trustworthiness judgements of faces correlate highly with general valence evaluations as well (see Oosterhof & Todorov, 2008; Todorov et al., 2008). Thus, it seems to be almost impossible to disentangle these features entirely.

Second, we manipulated expectations and the motivational state of our participants in a very indirect way. In our study, pictures of untrustworthy looking male targets were used to threaten the need to trust and to induce expectations of untrustworthiness, but these confrontations never resulted in actual interactions or consequences. Thus, participants were mere observers in our paradigm who did not experience victimization or exploitation per se. For this reason, future studies might want to threaten victim-sensitive individuals' need to trust in a more salient way, to be able to draw conclusive inferences about the motivational concerns of people high in victim sensitivity. One possibility to achieve this could be to thwart the need to trust through a direct experience of exploitation, for example in the context of a trust game (e.g., Berg et al., 1995; Gollwitzer & Rothmund, 2011). More specifically, one could think of an experimental design in which one half of the participants is being exploited by an interaction partner, whereas the other half experiences a neutral or positive social exchange. In our opinion, a manipulation like this should lead to even stronger effects than the ones obtained in the present study, and it would also provide additional insights into the underlying processes of attention allocation. Therefore, we consider it a useful avenue for future research.

Conclusion

The current findings provide first evidence that victim sensitivity influences the visual processing of social information related to (un)trustworthiness. Our results demonstrate that victim sensitivity predicts attention allocation towards positive expectancy violations, which are considered to be especially motivationally relevant for victim-sensitive individuals. Importantly, this attentional bias was not visible in all eye tracking measures: (high) victim sensitivity was only associated with longer first fixation durations on words that violated (vs. confirmed) untrustworthiness expectations, but not with longer dwell times or a higher fixation count. It therefore seems that victim sensitivity has an impact on earlier stages of the attentional processing of positive expectancy violations (prolonging the first fixation duration), while later stages (fixation count, dwell times) are rather unaffected. Furthermore, our study suggests that victim sensitivity is not associated with an attentional bias towards negative expectancy violations. In conclusion, the present research sheds light on the cognitive processes by which individuals high vs. low in victim sensitivity process violations and confirmations of (un)trustworthiness expectancies, and it adds to our understanding of the motivational concerns underlying victim sensitivity.

References

Aly, M., & Turk-Browne, N. B. (2016). Attention promotes episodic encoding by stabilizing hippocampal representations. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(4), E420–E429. https://doi.org/10.1073/pnas.1518931113

Berg, J., Dickhaut, J., & McCabe, K. (1995). Trust, reciprocity, and social history. *Games and Economic Behavior*, *10*(1), 122–142. https://doi.org/10.1006/game.1995.1027

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision*, *19*(3), 1–18. https://doi.org/10.1167/19.3.10

Brosch, T., & Van Bavel, J. J. (2012). The flexibility of emotional attention: Accessible social identities guide rapid attentional orienting. *Cognition*, *125*(2), 309–316. https://doi.org/10.1016/j.cognition.2012.07.007

Cabeza, R., Ciaramelli, E., Olson, I. R., & Moscovitch, M. (2008). The parietal cortex and episodic memory: An attentional account. *Nature Reviews Neuroscience*, *9*, 613–625. https://doi.org/10.1038/nrn2459

Chun, M. M., Golomb, J. D., & Turk-Browne, N. B. (2011). A taxonomy of external and internal attention. *Annual Review of Psychology*, *62*, 73–101. https://doi.org/10.1146/annurev.psych.093008.100427

Chun, M. M., & Turk-Browne, N. B. (2007). Interactions between attention and memory. *Current Opinion in Neurobiology*, *17*(2), 177–184. https://doi.org/10.1016/j.conb.2007.03.005

Cosmides, L., & Tooby, J. (1989). Evolutionary psychology and the generation of culture, part II: Case study: A computational theory of social exchange. *Ethology and Sociobiology*, *10*(1–3), 51–97. https://doi.org/10.1016/0162-3095(89)90013-7

Deubel, H., & Schneider, W. X. (1996). Saccade target selection and object recognition: Evidence for a common attentional mechanism. *Vision Research*, *36*(12), 1827–1837. https://doi.org/10.1016/0042-6989(95)00294-4

DeWall, C. N., Maner, J. K., & Rouby, D. A. (2009). Social exclusion and early-stage interpersonal perception: Selective attention to signs of acceptance. *Journal of Personality and Social Psychology*, *96*(4), 729–741. https://doi.org/10.1037/a0014634

Dietze, P., & Knowles, E. D. (2016). Social class and the motivational relevance of other human beings: Evidence from visual attention. *Psychological Science*, *27*(11), 1–11. https://doi.org/10.1177/0956797616667721

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

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

Fetchenhauer, D., & Huang, X. (2004). Justice sensitivity and distributive decisions in experimental games. *Personality and Individual Differences*, *36*(5), 1015-1029. https://doi.org/10.1016/S0191-8869(03)00197-1

Gerlach, T. M., Allemand, M., Agroskin, D., & Denissen, J. J. A. (2012). Justice sensitivity and forgiveness in close interpersonal relationships: The mediating role of mistrustful, legitimizing, and pro-relationship cognitions. *Journal of Personality*, *80*(5), 1373-1413. https://doi.org/10.1111/j.1467-6494.2012.00762.x

Gollwitzer, M., & Rothmund, T. (2009). When the need to trust results in unethical behavior: The Sensitivity to Mean Intentions (SeMI) model. In D. De Cremer (Ed.), *Psychological perspectives on ethical behavior and decision making* (pp. 135–152). Information Age Publishing.

Gollwitzer, M., & Rothmund, T. (2011). What exactly are victim-sensitive persons sensitive to? *Journal of Research in Personality*, *45*(5), 448–455. https://doi.org/10.1016/j.jrp.2011.05.003

Gollwitzer, M., Rothmund, T., Alt, B., & Jekel, M. (2012). Victim sensitivity and the accuracy of social judgments. *Personality and Social Psychology Bulletin*, *38*(8), 975–984. https://doi.org/10.1177/0146167212440887

Gollwitzer, M., Rothmund, T., Pfeiffer, A., & Ensenbach, C. (2009). Why and when justice sensitivity leads to pro- and antisocial behavior. *Journal of Research in Personality*, *43*(6), 999–1005. https://doi.org/10.1016/j.jrp.2009.07.003

Gollwitzer, M., Rothmund, T., & Süssenbach, P. (2013). The Sensitivity to Mean Intentions (SeMI) model: Basic assumptions, recent findings, and potential avenues for future research. *Social and Personality Psychology Compass*, *7*(7), 415–426. https://doi.org/10.1111/spc3.12041

Gollwitzer, M., Schmitt, M., Schalke, R., Maes, J., & Baer, A. (2005). Asymmetrical effects of justice sensitivity perspectives on prosocial and antisocial behavior. *Social Justice Research*, *18*(2), 183–201. https://doi.org/10.1007/s11211-005-7368-1

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Grühn, D., & Smith, J. (2008a). Characteristics for 200 words rated by young and older adults: Age-dependent evaluations of German adjectives (AGE). *Behavior Research Methods*, *40*(4), 1088–1097. https://doi.org/10.3758/BRM.40.4.1088

Grühn, D., & Smith, J. (2008b). Gruhn-Smith_2008_AGE.txt. Retrieved November 16, 2017 from Psychonomic Society Web Archive: http://www.psychonomic.org/ARCHIVE/

Heuer, A., & Schubö, A. (2018). Separate and combined effects of action relevance and motivational value on visual working memory. *Journal of Vision*, *18*(5), 1–14. https://doi.org/10.1167/18.5.14

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures.* Oxford University Press.

Inhoff, A. W., & Radach, R. (1998). Definition and computation of oculomotor measures in the study of cognitive processes. In G. Underwood (Ed.), *Eye guidance in reading and scene perception* (pp. 29–53). Elsevier.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). Motivated attention: Affect, activation, and action. In P. J. Lang, R. F. Simons & M. Balaban (Eds.), *Attention and orienting: Sensory and motivational processes* (pp. 97–135). Erlbaum.

Lavie, N., & Dalton, P. (2014). Load theory of attention and cognitive control. In A. C. Nobre & S. Kastner (Eds.), *The Oxford handbook of attention* (pp. 56–75). Oxford University Press.

Maltese, S., Baumert, A., Schmitt, M. J., & MacLeod, C. (2016). How victim sensitivity leads to uncooperative behavior via expectancies of injustice. *Frontiers in Psychology*, *6*, 2059. https://doi.org/10.3389/fpsyg.2015.02059

Mealey, L., Daood, C., & Krage, M. (1996). Enhanced memory for faces of cheaters. *Ethology and Sociobiology*, *17*(2), 119–128. https://doi.org/10.1016/0162-3095(95)00131-X

Mueller, S. T., & Piper, B. J. (2014). The Psychology Experiment Building Language (PEBL) and PEBL Test Battery. *Journal of Neuroscience Methods*, *222*, 250–259. https://doi.org/10.1016/j.jneumeth.2013.10.024

Oda, R. (1997). Biased face recognition in the Prisoner's Dilemma Game. *Evolution and Human Behavior*, *18*(5), 309–315. https://doi.org/10.1016/S1090-5138(97)00014-7

Oosterhof, N. N., & Todorov, A. (2008). The functional basis of face evaluation. *Proceedings of the National Academy of Sciences of the USA*, *105*(32), 11087–11092. https://doi.org/10.1073/pnas.0805664105

Proulx, T., Sleegers, W., & Tritt, S. M. (2017). The expectancy bias: Expectancy-violating faces evoke earlier pupillary dilation than neutral or negative faces. *Journal of Experimental Social Psychology*, *70*, 69–79. https://doi.org/10.1016/j.jesp.2016.12.003

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, *41*(1), 203–212. https://doi.org/10.1016/j.jrp.2006.02.001

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin*, *124*(3), 372–422. https://doi.org/10.1037/0033-2909.124.3.372

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *The Quarterly Journal of Experimental Psychology*, *62*(8), 1457–1506, https://doi.org/10.1080/17470210902816461

Rusting, C. L. (1998). Personality, mood, and cognitive processing of emotional information: Three conceptual frameworks. *Psychological Bulletin*, *124*(2), 165–196. https://doi.org/10.1037/0033-2909.124.2.165

Schmitt, M., Baumert, A., Gollwitzer, M., & Maes, J. (2010). The Justice Sensitivity Inventory: Factorial validity, location in the personality facet space, demographic pattern, and normative data. *Social Justice Research*, *23*, 211–238. https://doi.org/10.1007/s11211-010-0115-2

Singular Inversions. (2005). *FaceGen main software development kit* (version 3.1). Singular Inversions.

Singular Inversions. (2007). *FaceGen main software development kit* (version 3.2). Singular Inversions.

Summerfield, C., & Egner, T. (2009). Expectation (and attention) in visual cognition. *Trends in Cognitive Sciences*, *13*(9), 403–409. https://doi.org/10.1016/j.tics.2009.06.003

Süssenbach, P., Bohner, G., & Eyssel, F. (2012). Schematic influences of rape myth acceptance on visual information processing: An eye-tracking approach. *Journal of Experimental Social Psychology*, *48*(3), 660–668. https://doi.org/10.1016/j.jesp.2011.12.005

Süssenbach, P., Gollwitzer, M., Mieth, L., Buchner, A., & Bell, R. (2016). Trustworthy tricksters: Violating a negative social expectation affects source memory and person perception when fear of exploitation is high. *Frontiers in Psychology*, *7*, 1–12. https://doi.org/10.3389/fpsyg.2016.02037

Theeuwes, J. (2018). Visual selection: Usually fast and automatic; seldom slow and volitional. *Journal of Cognition*, *1*(1), 1–15. https://doi.org/10.5334/joc.13

Todorov, A., Pakrashi, M., & Oosterhof, N. N. (2009). Evaluating faces on trustworthiness after minimal time exposure. *Social Cognition*, *27*(6), 813–833. https://doi.org/10.1521/soco.2009.27.6.813

Todorov, A., Said, C. P., Engell, A. D., & Oosterhof, N. N. (2008). Understanding evaluation of faces on social dimensions. *Trends in Cognitive Sciences*, *12*(12), 455–460. https://doi.org/10.1016/j.tics.2008.10.001

Võ, M. L.-H., Conrad, M., Kuchinke, L., Urton, K., Hofmann, M. J., & Jacobs, A. M. (2009). The Berlin Affective Word List Reloaded (BAWL-R). *Behavior Research Methods*, *41*(2), 534–538. https://doi.org/10.3758/BRM.41.2.534

Willis, J., & Todorov, A. (2006). First impressions: Making up your mind after a 100-ms exposure to a face. *Psychological Science*, *17*(7), 592–598. https://doi.org/10.1111/j.1467-9280.2006.01750.x

Wolfe, J. M., Horowitz, T. S., & Michod, K. O. (2007). Is visual attention required for robust picture memory? *Vision Research*, *47*(7), 955–964. https://doi.org/10.1016/j.visres.2006.11.025

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and Emotion*, *18*(2), 129–166. https://doi.org/10.1007/BF02249397

Appendix A: Results of the competition conditions

Table A1

Means and Standard Deviations of Eye Movement Variables for Relevant Words Competition Conditions

Word	First fixation duration [ms]	Dwell time [ms]	Fixation count	Destination of the first saccade [%]
U face				
U word	260 (43)	487 (76)	2.05 (0.36)	23.86 (5.27)
T word	259 (46)	481 (76)	2.03 (0.35)	25.39 (6.55)
T face				
U word	259 (51)	492 (82)	2.09[b] (0.40)	25.54 (5.50)
T word	259 (46)	484 (79)	2.03[b] (0.35)	24.70 (5.52)

Note. U face = untrustworthy face, T face = trustworthy face, U word = untrustworthy word, T word = trustworthy word. Values reported for "destination of the first saccade" represent the percentage of trials in which the word was fixated first. Standard deviations are shown in parentheses.

[b] Significant difference between trustworthy and untrustworthy words in one face condition ($p < .05$, two-tailed).

Table A2

Correlations of Attentional Bias Scores with Victim Sensitivity

Competition Conditions

Bias score	VS	*p*	95% CI	
			LL	*UL*
U face				
First fixation duration	.05	.689	−.189	.283
Dwell time	.19	.111	−.049	.408
Fixation count	.21^{+}	.079	−.028	.426
Destination of the first saccade	−.06	.623	−.293	.179
T face				
First fixation duration	−.02	.878	−.255	.218
Dwell time	−.11	.370	−.338	.130
Fixation count	−.15	.212	−.373	.090
Destination of the first saccade	.04	.764	−.199	.274

Note. U face = untrustworthy face, T face = trustworthy face; VS = victim sensitivity; 95% CI = 95% confidence interval, *LL* = lower limit, *UL* = upper limit.

$^{+}$ Significant correlation (p < .05, one-tailed).

Appendix B: Results of the multilevel analysis

Table B1

Mixed Model Results

	First fixation duration				Dwell time				Fixation count			
Random effects	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*
Residual	19,098.23	231.22	82.60	<.01	43,339.79	523.21	82.83	<.01	0.78	0.01	82.83	<.01
Intercept	1,719.45	309.11	5.56	<.01	4,409.43	787.65	5.60	<.01	0.11	0.02	5.68	<.01
Fixed effects	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*
Intercept	262.56	5.13	51.19	<.01	482.04	8.19	58.87	<.01	2.03	0.04	49.21	<.01
Face	-0.46	2.36	-0.19	.85	-0.35	3.55	-0.10	.92	-0.01	0.02	-0.63	.53
Word	-4.33	2.36	-1.83	.07	15.19	3.55	4.28	<.01	0.10	0.02	6.92	<.01
ZVS	2.28	5.17	0.44	.66	-15.95	8.25	-1.93	.06	-0.08	0.04	-1.85	.07
Face x Word	0.49	4.72	0.10	.92	-11.38	7.09	-1.61	.11	-0.03	0.03	-1.03	.30
ZVS x Face	-4.91	2.38	-2.06	.04	-4.67	3.57	-1.31	.19	0.01	0.02	0.57	.57
ZVS x Word	2.74	2.38	1.15	.25	-4.10	3.57	-1.15	.25	-0.05	0.02	-3.07	<.01
ZVS x Face x Word	-6.85	4.76	-1.44	.15	-14.90	7.15	-2.09	.04	<0.01	0.03	0.07	.95
Model summary	Parameters	-2 Log-Likelihood			Parameters	-2 Log-Likelihood			Parameters	-2 Log-Likelihood		
Information criteria	10	174,305.14			10	186,605.96			10	36,025.44		

Note. Random effects: random intercepts were modeled for participants to account for the nested data structure. Fixed effects: two level-1 predictors (Face and Word) were included for face type (untrustworthy = -0.5, trustworthy = +0.5) and word type (untrustworthy = -0.5, trustworthy = +0.5). At level 2, victim sensitivity (ZVS; *z*-standardized) as well as the respective interaction terms were entered.

Table B2

Mixed Model Results Separately for Face Conditions

	First fixation duration				Dwell time				Fixation count			
					U face							
Random effects	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*
Residual	20,069.69	344.52	58.25	<.01	42,941.83	735.04	58.42	<.01	0.79	0.01	58.42	<.01
Intercept (subject)	1,714.04	326.17	5.26	<.01	4,474.48	835.03	5.36	<.01	0.11	0.02	5.48	<.01
Fixed effects	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*
Intercept	262.82	5.27	49.88	<.01	482.23	8.43	57.20	<.01	2.04	0.04	49.11	<.01
Word	-4.57	3.42	-1.34	.18	20.89	4.99	4.19	<.01	0.12	0.02	5.60	<.01
ZVS	4.74	5.31	0.89	.38	-13.60	8.49	-1.60	.11	-0.08	0.04	-1.94	.06
ZVS x Word	6.15	3.45	1.78	.08	3.36	5.03	0.67	.50	-0.05	0.02	-2.20	.03
					T face							
Random effects	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*	Variance	*SE*	Wald *Z*	*p*
Residual	18,097.46	310.62	58.26	<.01	43,817.06	749.91	58.43	<.01	0.77	0.01	58.43	<.01
Intercept (subject)	1,754.69	329.84	5.32	<.01	4,262.82	800.43	5.33	<.01	0.12	0.02	5.51	<.01
Fixed effects	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*	Estimate	*SE*	*t*	*p*
Intercept	262.34	5.30	49.52	<.01	481.86	8.25	58.38	<.01	2.03	0.04	47.58	<.01
Word	-4.08	3.25	-1.25	.21	9.49	5.04	1.88	.06	0.09	0.02	4.19	<.01
ZVS	-0.19	5.34	-0.04	.97	-18.29	8.32	-2.20	.03	-0.07	0.04	-1.69	.10
ZVS x Word	-0.71	3.27	-0.22	.83	-11.55	5.08	-2.27	.02	-0.05	0.02	-2.14	.03

Note. U face = untrustworthy face, T face = trustworthy face. Random effects: random intercepts were modeled for participants to account for the nested data structure. Fixed effects: one level-1 predictor (Word) was included for word type (untrustworthy = -0.5, trustworthy = +0.5). At level 2, victim sensitivity (ZVS; *z*-standardized) as well as the respective interaction term was entered.

APPENDIX

Contributions to the aims of the RTG 2271

The present dissertation project was part of the research-training group "GRK | RTG 2271 – Breaking Expectations" (Project 9, funded by the Deutsche Forschungsgemeinschaft, DFG). The overall aim of the RTG is to study in an interdisciplinary perspective when and how expectations persist and when changes in expectations manifest. In the following paragraphs, it is briefly summarized how the five studies of the present dissertation contribute to these aims.

In our natural environment, we usually encounter stimuli, which are embedded in visual scenes. These scenes can help humans to deal with the large amount of incoming visual information because they allow the organism to generate expectations about stimuli that are worth attending. The studies of this dissertation shed light on how observers use visual contexts to generate such predictions and on how persistent these expectations are.

Study I showed that humans use knowledge they have acquired in former encounters with similar scenes to predict the most promising item to attend to in an upcoming scene. In a visual search task in the laboratory, participants responded faster in visual contexts that repeated compared to contexts that were novel. In addition, they also moved their eyes more efficiently to the target when they encountered repeated contexts. These results suggest that participants use repeated visual contexts to learn to predict the target location.

Study I also revealed that visual contexts are especially used for specifying promising items when they predict a high reward. Context features predicting a high reward boosted the performance advantages observed with repeated contexts. This result suggests that the prediction of reward facilitates the generation of expectations about potential target locations.

Study II demonstrated that expectations about potential target locations were quite persistent, since performance benefits were observed even after many encounters with repeated contexts. Further experiments showed that participants could use even a very limited part of the visual contexts to learn to predict the target location (Study III) and that observers use also contexts that change dynamically for specifying promising items to attend to (Study IV). These results suggest that observers use regularities in the visual context to generate expectations about promising items in their visual environment, which influence their behavior even after many encounters.

Finally, the last study of this dissertation (Study V) was a collaboration project within the RTG ("Treasure-Box" funding for Projects 9 and 4). This study investigated how an observer's personality modulates the use of visual contexts for specifying relevant visual information. Results showed that observers differ in how they use contexts for specifying relevant visual information and suggested that an observer's personality might be one factor explaining these differences.

In sum, this dissertation project showed that observers use visual contexts to generate persistent expectations about promising items to attend to and that they especially use contexts that are motivationally relevant for an individual – a behavior that can be determined by an individual's personality.

Author contributions

Study I: Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision, 19*(3), 1-18. https://doi.org/10.1167/19.3.10

- AS and DK designed the experiment. DK collected the data. NB analyzed the data. NB and AS wrote the manuscript.

Study II: Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision Research, 171*, 53–63. https://doi.org/10.1016/j.visres.2020.03.010

- NB and AS designed the experiment. NB collected the data. NB and JT analyzed the data. NB, AS, and JT wrote the manuscript.

Study III: Bergmann, N., & Schubö, A. (in preparation). Local and global context repetitions in contextual cueing: The influence of reward.

- NB and AS designed the experiment. NB collected and analyzed the data. NB and AS wrote the manuscript.

Study IV: Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on?: Adapting to color while searching for shape. *Attention, perception & psychophysics, 16*(3). https://doi.org/10.3758/s13414-019-01858-6

- NB and AS designed the experiments. JT and NB analyzed the data. NB, JT and AS wrote the manuscript.

Study V: Buchholz, M., Bergmann, N., Schubö, A., & Gollwitzer, M. (submitted). Victim Sensitivity Predicts Attention Allocation Towards Violations of Untrustworthiness Expectancies.

- MB, NB, AS, and MG designed the experiment. MB and NB collected and analyzed the data. MB, NB, AS, and MG wrote the manuscript.

Zusammenfassung in deutscher Sprache

In unserer Umwelt erscheinen visuelle Stimuli üblicherweise in Kontexten aus anderen Stimuli, welche in der Regel nicht zufällig angeordnet sind, sondern Regularitäten folgen. Diese Regularitäten können für das visuelle System sehr nützlich sein, um das Problem der begrenzen Verarbeitungskapazität zu bewältigen, da sie helfen, die Aufmerksamkeit auf verhaltensrelevante Stimuli zu lenken. Es gibt immer mehr Evidenz dafür, dass Beobachter wiederholte Kontexte für die Aufmerksamkeitslenkung verwenden und dass sich Beobachter an dynamische Veränderungen in ihrem visuellen Umfeld anpassen. Allerdings beinhalten visuelle Kontexte in unserer natürlichen Umgebung häufig Merkmale, die Belohnung vorhersagen, und über den Einfluss solcher Kontexte auf die Aufmerksamkeitslenkung ist bislang wenig bekannt. Außerdem ist unklar, wie Beobachter ihr Verhalten an Kontextmerkmale anpassen, die nicht relevant für die Aufgabe sind. Darüber hinaus ist wenig zu individuellen Unterschieden in den Effekten von Kontexten bekannt. Diese Forschungslücken werden in dieser Dissertation adressiert. Die vorliegende Dissertation untersucht in fünf Studien, wie unterschiedliche Arten von kontextuellen Regularitäten in das Verhalten integriert werden und wie diese Regularitäten die visuelle Aufmerksamkeit lenken.

Der Hauptteil dieser Dissertation (Studien I-III) konzentriert sich auf visuelle Kontexte, welche sich über die Zeit hinweg nicht verändern und auf welche Beobachter wiederholt stoßen („wiederholte Kontexte“). Dazu verwendeten die Studien I-III das „Contextual Cueing“ Paradigma (Chun & Jiang, 1998), ein Paradigma einer visuellen Suche, in welchem die Teilnehmer einen Zielreiz („Target“) unter einer Kontextkonfiguration aus Distraktoren finden sollen. In den Studien I und II wiederholte sich die Hälfte dieser Konfigurationen während der Experimente, wogegen die andere Hälfte für jeden Durchgang neu generiert wurde. In beiden Studien wurde beobachtet, dass die Teilnehmer in wiederholten Kontexten schneller als in neuen Kontexten antworteten. Dieser Effekt entwickelte sich im Verlauf der Experimente und ist als *„Contextual Cueing (CC)“ Effekt* bekannt.

Die Teilnehmer antworteten in wiederholten Kontexten nicht nur schneller als in neuen Kontexten, sondern sie bewegten auch ihre Augen effizienter zum Target. Dies deutet darauf hin, dass die Aufmerksamkeitslenkung durch die wiederholten Kontexte erleichtert wurde und dass die Teilnehmer die Kontexte verwendeten, um das Target zu finden. Studie III zeigte, dass die Teilnehmer nicht nur vollständig wiederholte Kontexte verwenden konnten, sondern auch Kontexte, in welchen sich nur eine kleine Menge der Kontextinformation wiederholte. Wenn nur drei Distraktoren wiederholten wurden, zeigten die Teilnehmer im Grunde einen ähnlichen CC-Effekt, wie er bei vollständig wiederholten Kontexten beobachtet wurde. Dieses überraschende Ergebnis legt nahe, dass bereits eine kleine Menge an wiederholter Kontextinformation ausreicht, um die Aufmerksamkeit an den Ort des Targets zu lenken.

Als eine wichtige Neuerung zu bisherigen Studien untersuchten Studien I-III weiterhin die Rolle von Kontextmerkmalen, welche eine Belohnung signalisieren. In Studie I wurde die Hälfte der Objekte im Kontext in einer Farbe präsentiert, welche irrelevant für die Aufgabe war und eine niedrige, mittlere oder hohe Belohnung anzeigte. Die Teilnehmer zeigten einen verstärkten CC-Effekt in Kontexten, in denen die Farbe eine hohe Belohnung anzeigte. Der verstärkte CC-Effekt war auf schnellere Reaktionszeiten in wiederholten Kontexten mit hoher Belohnung zurückzuführen. Reaktionszeiten in neuen Kontexten wurden nicht von der Belohnung beeinflusst. Außerdem bewegten die Teilnehmer ihre Augen effizienter zum Target in wiederholten Kontexten, welche eine hohe Belohnung signalisierten. Dies deutet darauf hin, dass die Belohnung den CC-Effekt durch eine Erleichterung der Aufmerksamkeitslenkung verstärkte.

Studie II replizierte, dass der CC-Effekt in Kontexten, die eine hohe Belohnung vorhersagen, verstärkt ist. In Studie II war die Belohnung allerdings an ein Merkmal gekoppelt, welches relevant für die Aufgabe war. Die Belohnung wurde nämlich an die vorherrschende Orientierung der Distraktoren gebunden. Zudem untersuchte Studie II genauer, wann die Belohnungseffekte auftraten und wie lange sie fortbestanden. Die Ergebnisse zeigten, dass eine Belohnung den CC-Effekt anhaltend verstärkt und nicht lediglich zu einem früher auftretenden, aber asymptotisch ähnlich starkem Effekt führt, wie es vorherige Studien annahmen (vgl. Tseng & Lleras, 2013). Studie III untersuchte, ob Farben, welche eine Belohnung vorhersagten, die Performanz in teilweise wiederholten und vollständig wiederholten Kontexten auf die gleiche Art beeinflussten. Überraschenderweise hatte eine Belohnung keinen Einfluss auf den CC-Effekt in Studie III, weder in teilweise wiederholten noch in vollständig wiederholten Kontexten. Es gab Hinweise darauf, dass die meisten Teilnehmer die Farbe nicht mit der Belohnung assoziiert hatten, was vermutlich am Einschluss der teilweise wiederholten Kontexte im Experiment lag. Daher steht der fehlende Effekt von Belohnung in Studie III nicht zwingend im Widerspruch zu den Ergebnissen von Studien I und II. Zusammengefasst zeigt der erste Teil dieser Dissertation folglich, dass Kontexte, welche eine hohe Belohnung vorhersagen, beim Lernen von Kontextkonfigurationen priorisiert werden. In wiederholten Kontexten, die eine hohe Belohnung vorhersagen, wird die Aufmerksamkeit effizienter zum Target gelenkt, auch nach vielen Kontextwiederholungen.

Der zweite Teil dieser Dissertation (Studie IV) untersucht, wie Beobachter Kontexte verwenden, welche sich in einer vorhersagbaren Abfolge dynamisch verändern. Dazu verwendete Studie IV das „Adaptive Choice Visual Search“ Paradigma (ACVS, Irons & Leber, 2016) und zeigte, dass Beobachter ihre Wahl zwischen zwei Targets an eine vorhersagbare Farbveränderung anpassen. Die visuellen Kontexte in Studie IV enthielten Elemente in zwei Farbgruppen und das Verhältnis der Elemente in diesen Gruppen veränderte sich mit jedem Durchgang. Die Teilnehmer konnten frei zwischen zwei Targets wählen, wobei sich in beiden Farbgruppen jeweils ein Target befand. Im Gegensatz zu bisherigen Studien war Farbe allerdings eine irrelevante Merkmalsdimension in dieser Aufgabe, da die Targets durch ihre Form definiert waren. Die Ergebnisse zeigten, dass die Teilnehmer ihre Targetauswahl an die Farbveränderung anpassten. Sie bevorzugten das Target aus der kleineren Farbgruppe, obwohl Farbe irrelevant war. Diese Ergebnisse legen nahe, dass sich Beobachter nicht nur an statische Kontextwiederholungen anpassen, wie Studien I-III zeigten, sondern dass sie auch kontextuelle Veränderungen in ihr Verhalten in der visuellen Suche integrieren (vgl. Wang & Theeuwes, 2020).

Der dritte und letzte Teil dieser Dissertation (Studie V) untersucht Kontexte der sozialen Wahrnehmung und verbindet die Untersuchung visueller Kontexte mit den Disziplinen der Sozial- und Persönlichkeitspsychologie. Die Teilnehmer sahen Kontexte mit einem vertrauenswürdigen oder unvertrauenswürdigen Gesicht, umgeben von vier Wörtern, welche entweder kongruent, inkongruent oder neutral zu dem Kontext waren. Studie V untersuchte, wie die Kontexte die Aufmerksamkeitsallokation zu kongruenten und inkongruenten Stimuli beeinflussten und wie die Persönlichkeit der Beobachter die Aufmerksamkeitsallokation modulierte. Dafür wurde das Persönlichkeitsmerkmal „Opfersensibilität“ (Gollwitzer, Rothmund & Süssenbach, 2013) als vielversprechendes Merkmal ausgewählt. Die Ergebnisse zeigten, dass sich die Aufmerksamkeitsallokation, welche durch die Augenbewegungen der Teilnehmer gemessen wurde, zwischen den Kontexten unterschied. Die Teilnehmer widmeten vertrauenswürdigen Wörtern generell mehr Aufmerksamkeit als unvertrauenswürdigen Wörtern (vertrauenswürdige Wörter wurden länger angesehen und häufiger fixiert). Dieser Unterschied war tendenziell jedoch größer in unvertrauenswürdigen Kontexten, was nahelegt, dass die hier inkongruenten vertrauenswürdigen Wörter in der Aufmerksamkeitsallokation priorisiert wurden. Darüber hinaus korrelierte Opfersensibilität mit einer erhöhten Aufmerksamkeitsallokation zu inkongruenten Stimuli, allerdings nur in unvertrauenswürdigen Kontexten. Diese Ergebnisse zeigen, dass Kontexte der sozialen Wahrnehmung die Verarbeitung von kongruenten und inkongruenten visuellen Informationen beeinflussen und dass die Persönlichkeit der Beobachter ein wichtiger Faktor für die Effekte der Kontexte ist.

Insgesamt zeigen die fünf Studien der vorliegen Dissertation, dass das visuelle System erstaunlich empfindlich auf Regularitäten im visuellen Kontext reagiert. Es ist ziemlich effizient darin, wiederholte Kontexte zu extrahieren, um die Aufmerksamkeit an relevante Orte zu lenken, wenn der Kontext erneut angetroffen wird (Studien I und II). Außerdem benötigt es lediglich eine begrenzte Menge an wiederholter Kontextinformation, um einen Vorteil aus den Kontexten ziehen zu können (Studie III). Auch Belohnungen, welche von Kontextmerkmalen vorhergesagt werden, werden berücksichtigt, um Kontexte mit einer hohen Belohnung zu priorisieren. Das visuelle System passt sich zudem an dynamische Veränderungen in den Kontexten an (Studie IV) und verwendet, abhängig von der Persönlichkeit der Beobachter, Kontexte der sozialen Wahrnehmung um die Verarbeitung inkongruenter Stimuli zu priorisieren (Studie V). Die vorliegende Dissertation legt daher nahe, dass der visuelle Kontext entscheidend für die Aufmerksamkeitslenkung in zahllosen alltäglichen Situationen ist. Erfreulicherweise können wir den visuellen Kontext nutzen, was unserem visuellen System erlaubt, seine begrenzte Verarbeitungskapazität zu bewältigen.

Curriculum Vitae

Die Seiten 181 – 182 enthalten persönliche Daten
und sind deshalb nicht Teil der Veröffentlichung.

Publikationsliste

Publikationen

Bergmann, N., Tünnermann, J., & Schubö, A. (2020). Reward-predicting distractor orientations support contextual cueing: Persistent effects in homogeneous distractor contexts. *Vision Research, 171*, 53-63.

Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Which search are you on? Adapting to color while searching for shape. *Attention, Perception & Psychophysics*, *16*(3).

Bergmann, N., Koch, D., & Schubö, A. (2019). Reward expectation facilitates context learning and attentional guidance in visual search. *Journal of Vision 19*(3), 1-18.

Bergmann, N., Schacht, S., Gnewuch, U., & Maedche, A. (2017). Understanding the Influence of Personality Traits on Gamification: The Role of Avatars in Energy Saving Tasks. In *Proceedings of the 38th International Conference on Information Systems (ICIS)*. Seoul, ROK: AISeL.

Schacht, S., Keusch, F., **Bergmann, N.**, & Morana, S. (2017). Web Survey Gamification: Increasing Data Quality in Web Surveys by Using Game Design Elements. In *Proceedings of the 25th European Conference on Information Systems (ECIS)* (pp. 2907–2917).

Präsentationen auf wissenschaftlichen Konferenzen

Buchholz, M., **Bergmann, N.**, Schubö, A., Gollwitzer, M. (2019). Expectations of (Un)Trustworthiness Influence Attention Guidance. Talk at the *17th Conference of the Social Psychology Section (17. Tagung der Fachgruppe Sozialpsychologie, FGSP 2019)*, Cologne, Germany.

Bergmann, N., Tünnermann, J., & Schubö, A. (2019). Adapting target selection in dynamically changing visual scenes. *Journal of Vision*, 19(10), 232c. Poster presented at the *Annual Meeting of the Vision Sciences Society (VSS)*, St. Pete Beach, Florida, USA.

Bergmann, N., Koch, D., & Schubö, A. (2018). Reward-predicting stimuli accelerate contextual cueing and modulate eye movements. *Journal of Vision*, 18(10), 1202. Poster presented at the *Annual Meeting of the Vision Sciences Society (VSS)*, St. Pete Beach, Florida, USA.

Bergmann, N., Koch, D., & Schubö, A. (2018). Modulation of context learning by anticipated reward magnitude. Poster presented at the *Conference of Experimental Psychologists (Tagung experimentell arbeitender Psychologen, TeaP)*, Marburg, Germany.

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Eigenständigkeitserklärung

Hiermit versichere ich, die vorliegende Dissertation

„How the visual environment shapes attention: The role of context in attention guidance“

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.

Marburg, September 2020

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(Nils Bergmann)