Overcoming The Blink:
The Effect of Training on the Attentional Blink

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1 Abstract

One of the major topics in attention literature is the attentional blink (AB), which demonstrates a limited ability to identify the second of two targets (T1 and T2) when presented in close temporal succession (200-500 ms). Two decades of research have suggested that the AB is caused by structural limitations in target processing and is, as such, resistant to training. In contrast to this view, it was recently found that the AB was eliminated after just one hour of training with a color-salient T2 (Choi et al., 2012). However, the underlying mechanism of the training effect, as well as the AB itself, is as of yet still poorly understood. In the current thesis, we investigated the effect of training in two ways: First, we employed pupil dilation deconvolution to track any training-induced changes in the amount and onset of attentional processing of target stimuli. Second, we presented and tested a cognitive model, proposing that the training effect is caused by a shift in memory strategy. In addition to replicating the effect of the color-salient training, we found that training without a salient target, but with a consistent short inter-target interval was already sufficient to eliminate the AB. Pupil dilation revealed an earlier attentional allocation to T1 after training. The model was successful in explaining the training effect, as well as predicting the effect of a letter-mask training on the AB. We conclude that two complementary mechanisms play a role in overcoming the AB: temporal expectations and a switch in memory strategy. The results provide further evidence against limited-capacity theories of the AB.

2 Acknowledgements

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4 Introduction

The human mind is limited in the amount of information it can process within a short time frame. A well-known phenomenon that seems to reflect this limitation is the attentional blink (AB): When two targets are presented in close temporal succession (~200-500 ms) in a rapid serial visual presentation (RSVP), the second target is often not correctly reported (Raymond, Shapiro, & Arnell, 1992). The AB has been replicated in hundreds of experiments, with different types of stimuli and in various modalities (Martens & Wyble, 2010).

Despite more than two decades of research on the AB, no consensus has been reached about its underlying mechanisms. Initially, the AB was suggested to be the consequence of limited resources in a late stage of visual processing (e.g. Chun & Potter, 1995; Jolicœur & Dell'Acqua, 1999; Dux, Asplund & Marois, 2008). These limited-capacity theories propose that target detection is followed by working memory consolidation, after which targets are available for report. The latter processing stage has been suggested to be capacity-limited. Therefore, when the first target (T1) is consolidated, a following target (T2) cannot be processed in working memory, thereby causing an AB.

However, several findings have suggested that theories of limited capacity are not sufficient. First, it has been found that the AB can be reduced through a decreased focus on target identification. For example, Olivers and Nieuwenhuis (2005) found an improved T2 detection when participants were instructed to think about their holidays or shopping requirements, or to listen to music. Similarly, Taatgen, Juvina, Schipper, Borst, and Martens (2009) found a reduced AB when participants performed a concurrent red dot detection task. Second, multiple targets in fast succession can be detected when there is no intervening distractor (Di Lollo, Kawahara, Shahab Ghorashi, & Enns, 2005). Therefore, more recent models assume that the AB is not caused by limited resources, but is instead a detrimental side effect of an attentional strategy (Nieuwenstein, Chun, Van der Lubbe, & Hooge, 2005; Nieuwenstein & Potter, 2006; Olivers, van der Stigchel, & Hulleman, 2007; Taatgen et al., 2009; Wyble, Bowman, & Nieuwenstein, 2009).

Although the theoretical focus shifted from memory consolidation to executive control, recent models still view the AB as a product of structural limitations. This view has been reinforced by several unsuccessful attempts to reduce the AB through repetitive training with the AB task (Braun, 1998; Maki and Padmanabhan, 1994, Taatgen et al., 2009). In contrast, however, a recent experiment has shown that the AB can be eliminated with just one hour of training (Choi, Chang, Shibata, Sasaki, & Watanabe, 2012). In the experiment of Choi et al. (2012), participants performed a pre-training, training and post-training AB task for three consecutive days. In the training task, the second target was presented in red and always appeared 200 ms after T1. Choi et al. found that the AB was eliminated after one training day. Surprisingly, the reduced AB persisted several months after training and was generalizable to multiple inter-target lags. In addition, the color-salient training improved performance on a target-mask task in which participants had to identify a target digit presented quickly before or after a letter distractor.

Choi et al. (2012) argued that the elimination of the AB is not the result of increased processing abilities, but of fundamental attention-based improvements. This claim is supported by evidence from an fMRI experiment in which they found differences in dorsolateral prefrontal activity when comparing the processing of targets at short lags with the processing at long lags post-training. According to Choi et al., if the training induced a general enhancement in target processing, such differences would not be observed. It is questionable though how strongly the neuroimaging evidence supports this claim, given the limited temporal resolution of fMRI.

In contrast, Tang, Badcock and Visser (2013) suggested that the effect of training is due to the strengthening of temporal expectations that arise from the fixed temporal locations of the targets during the training. Previous studies have shown that knowledge about the temporal position of T2 can significantly reduce the AB. For example, Hilkenmeier and Scharlau (2010) found an improved T2 identification when T1 contained a valid cue about the lag between the two targets. Similarly, Martens and Johnson (2005) found a reduced AB when a fixation cue prior to the trial indicated the temporal position of T2. However, they also found that the constant presentation of the same lag did not lead to a better performance compared to a control group who received varying lags.

In Choi et al. (2012), T1 was always the second item of the stream and T2 was always presented at either 200 (lag 2) or 600 ms (lag 6) after T1. According to Tang et al., the repeated presentation of the color-salient T2 at lag 2 during the training highlighted this consistency, thereby creating expectations about the onset of the targets. Supporting their hypothesis, the authors showed that the training effect was significantly reduced when the timing of target onset was varied in either the training or the assessment task. Furthermore, they found a decrease in performance at the longer lag after the color-salient training, but an attenuation of this decrease after the variable task condition and the variable training condition. However, the temporal expectation account can neither explain why the effect of training was generalizable to multiple lags (Choi et al., experiment 5) and another task (Choi et al., experiment 6), nor can it exclude that a variable training or task just needs a longer training duration to attain a similar improvement in performance.

Thus, while it is clear that the AB can be attenuated through a simple training, the underlying mechanism of this training effect is not yet understood. In the studies reported in the current thesis, we aimed to investigate training-induced changes in several ways. First, our goal was to uncover changes in attention by measuring pupil dilation in the AB task before and after the training (Experiment 1). Through deconvolution of the dilation, we were able to reveal training-induced changes in attention at a high temporal resolution. In the experiment, the color-salient training was contrasted with two control conditions in which the second target was not salient: A training with just lag 2 trials, and one with lag 2 and lag 6 trials. Second, we present a new model of the AB, based on the primitive elements theory of cognitive skill (PRIMs) (Taatgen, 2013). The model proposes that the training effect is the result of a switch in memory strategy. Third, we investigated the validity of the model by testing participants on a new training paradigm that promotes the use of a memory strategy that is effective in the AB task (Experiment 2).

5 Experiment 1

Changes in the size of the pupil have been linked to dynamical changes in attentional capacity (e.g., Kahneman, 1973; Verney, Granholm & Marshall, 2004). Pupil dilation is thought to reflect changes in activity of the Locus Coeruleus (LC): a nucleus which is the hub of the noradrenergic system (for reviews see (Laeng, Sirois, & Gredebäck, 2012; Sara, 2009)). Given that phasic activity of the LC is associated with the processing of task-relevant stimuli (Aston-Jones & Cohen, 2005; Dayan & Yu, 2006), task-evoked pupil dilation is thought to reflect changes in the attentional detection system (Privitera, Renninger, Carney, Klein, & Aguilar, 2008).

Pupillary responses are relatively slow (~1 Hz), such that they overlap when relevant events quickly follow each other. Therefore, pupil measurements have traditionally been limited to slow tasks in which events are sufficiently spaced in time. However, the recently developed pupil dilation deconvolution method makes it possible to analyze a fast-paced task like the AB task (~10 Hz) (Wierda, van Rijn, Taatgen, & Martens, 2012). In the deconvolution method, it is assumed that each event (e.g. a stimulus) triggers a pupillary response that can be described with an Erlang gamma function (Fig. 1a; Hoeks & Levelt, 1993). The size of this response depends on the strength of the event. Because of the additive nature of the pupil (Hoeks & Levelt, 1993), the measured pupil dilation during a task is regarded as the sum of responses to separate events (Fig. 1b). This property makes it possible to deconvolve a pupil dilation signal into isolated target-specific attentional activity. In this way, the strength and timing of attention allocated to a target can be revealed. In addition, the deconvolution method allows for the extraction of expectation effects, which can arise in the absence of an actual target (Wierda et al., 2012).

Using a refined version of this deconvolution method, our goal in the first experiment is to address the changes in target-related attentional allocation as an effect of the color-salient training. Two additional training tasks will control for any learning effects, which leaves us with three training conditions: First, the Color-Salient training condition, resembling the training of Choi et al. (2012), contains a red second target, and only short-lag trials. Second, the Lag-2 training condition contains no salient target, thus all stimuli are presented in black, and again, there are only short-lag trials (Choi et al., 2012). Third, the Lag-2&6 training is similar to the Lag-2 condition with the exception that the lags between the targets are variable, i.e., a short and a long lag. It is expected that the Color-Salient training will enhance performance at the short lag, such that the AB will be eliminated. Furthermore, if performance at the long lag is decreased after the Color-Salient training (Tang et al., 2013), this will reinforce the theory that temporal expectations underlie the training effect. Because the salient target is seen as a crucial factor in the training effect, no effects are expected in the Lag-2 condition and the Lag-2&6 condition.

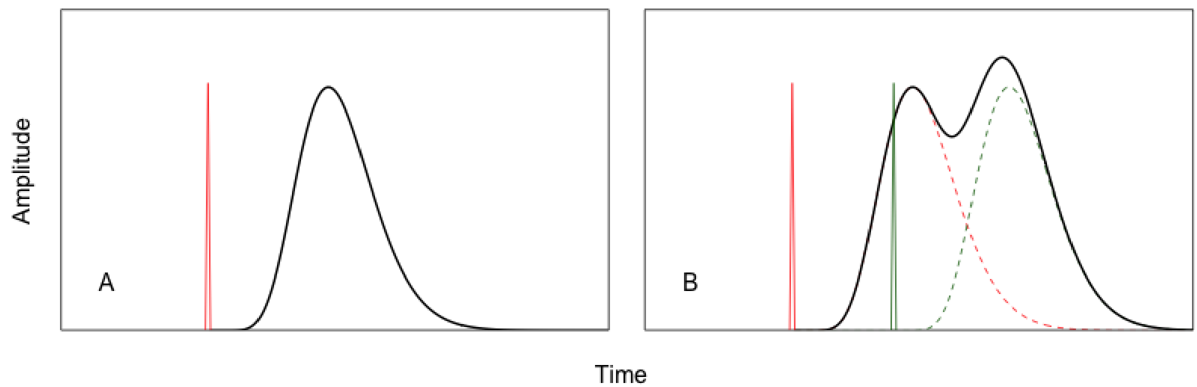

Figure 1: Convolution, as proposed by Hoeks & Levelt (1993). Figure A) shows the pupillary response (black line), modeled by the Erlang gamma function, as a response to an event (red pulse). In Figure B), there are two equally strong events (red and green pulses), triggering an identical pupillary response (dashed red and green lines). The resulting pupil dilation is the sum of these responses (black line).

Given that we do not expect an eliminated AB after both control conditions, the expectations with regard to training-induced changes in pupil dilation will focus on the Color-Salient condition. Here, we expect that if less cognitive effort is needed as a result of general enhanced processing post-training, this may be reflected in decreased amplitudes of the peaks that are associated with attentional target processing post-training compared to pre-training. In addition, if the training induces either an attentional strategy change (Choi et al., 2012) or strengthens temporal expectations (Tang et al., 2013), this could result in temporal changes in attentional allocation to the targets, as reflected in shifts of peak latencies. Finally, if training induces temporal expectations, we expect to observe increased expectation effects, i.e., increased attentional pulses, during single-target trials at the time points when a target is expected to occur. Such a finding would substantiate the temporal expectations theory.

5.1 Method

A total of 81 students of the University of Groningen participated in the experiment in return for a €15.- payment or course credits. All participants had normal or corrected-to-normal visual acuity, and no history of neurological problems. All participants performed a similar pre- and post-training task, but three types of training were provided: the Color-Salient training (26 participants; 15 female; mean age = 21.7 (ranging 19-26)), the Lag-2 training (29 participants; 21 female; mean age = 21.4 (ranging 18-29)), and the Lag-2&6 training (26 participants; 16 female; mean age = 20.1 (ranging 18-25)). After preprocessing the eye data, four participants were excluded from the pupil dilation analyses due to too many artifacts. After exclusion, 25 participants remained in the Color-Salient condition, 27 in the Lag-2 condition, and 25 in the Lag-2&6 condition. The Psychology Ethical Committee of the University of Groningen approved the experimental protocol, and written informed consent was obtained from each participant prior to the experiment.

5.1.1 Behavioral

AB task. The experiment was generated using E-prime 2.0 and presented on a 19-inch computer screen with a 100 Hz refresh rate. Participants performed an AB task in the practice block, the pre-training block, and the post-training block. The practice block contained 3 trials, and the pre- and post-training blocks contained 90 trials each. In these blocks, each trial contained a Rapid Serial Visual Presentation (RSVP) of 32 items, which was presented in the middle of the screen at a rate of ~10 Hz with no inter-stimulus interval. Target stimuli consisted of uppercase consonants, excluding "Q", "V", and "Y", whereas distractor stimuli consisted of digits ranging 2-9. All stimuli were presented in black, 18-point Courier New on a white background. On a third of the trials, one target was presented, whereas on the remainder of the trials two targets were presented. The first target (T1) was always presented as the sixth stimulus of the RSVP. On dual-target trials, the second target (T2) was presented as either the eighth stimulus (lag 2) or the twelfth stimulus (lag 6). All types of trials (single-target, lag 2, and lag 6) were presented randomly and equally often. In addition, stimuli were selected pseudo-randomly, with the constraints that target letters were not repeated within a single trial and that distractor digits were not presented twice in succession. Preceding the stream, a fixation cross was presented for 850 ms. To ensure that participants would stay fixated on the middle of the screen until the end of the trial, a comma or a dot was shown for 100 ms following the last distractor. This comma or dot had to be identified in addition to the target letters and allowed for recording the pupil response to the second target. After each trial, participants were prompted to type in the letters on the keyboard in the order they had seen them or to press spacebar when no target was observed. Hereafter, participants had to indicate whether the last character was a comma or a dot.

Training task. The training block in each condition contained 450 trials. The trials were similar to the ones in the pre- and post-training block, except for the following differences. The RSVP consisted of 10 items and T1 was always presented as the second item of the stream. The Color-Salient training consisted of lag-2 trials only and T2 was always presented in red. The Lag-2 training also consisted of lag-2 trials only, however all stimuli were presented in black. In addition, the Lag-2&6 training contained both lag-2 and lag-6 trials, presented randomly and equally often. Here, all stimuli were also presented in black.

Participants could take a short break in between blocks and halfway through the training block. They completed the experiment in approximately 70 minutes.

Statistical methods. Statistical analyses were performed using the *lmerTest* package (Kuznetsova, Brockhoff, & Christenen, 2013) in R (version 2.14.2; (R Development Core team, 2012)). The behavioral data were analyzed using Generalized Linear Mixed Models (GLMM), and Tukey's HSD tests were performed as post-hoc comparison tests. In all models, 'participants' was entered as random intercept, and fixed factors were included based on theoretical grounds. Trials in which T1 and T2 were identified correctly but reported in reversed order were also considered correct. Furthermore, tests for overdispersion did not reveal any problems.

5.1.2 Pupil dilation

Pupil dilation was measured using the EyeLink 1000 eye tracker (www.sr-research.com). Prior to the experiment, the eye tracker camera was configured to track the left eye, and the eye tracker was then calibrated. Viewing distance was ~50 cm. Pupil dilation was measured during the pre- and post-training blocks. However, participants kept their head in a chin-rest during all blocks to keep task conditions comparable.

Pre-processing. The pupil data were sampled at 250 Hz and down-sampled to 50 Hz. The data of each trial were time-locked to the onset of T1. Segments containing eye blinks were recovered using linear interpolation or excluded based on semi-automatic inspection. The average pupil size during the 200 ms before stream onset was used as a baseline, and the data were normalized by applying the following formula:

$$Xnorm = \frac{X - Baseline}{Baseline}.$$

Attentional pulses were estimated by using the pupil dilation deconvolution method (Wierda et al., 2012). Per combination of participant and condition, 80 pulses were modeled, starting 400 ms before stream onset. The set of pulse strengths $i = \{w1, w2, w3, \ldots, w78, w79, w80\}$ was convolved with the Erlang gamma function $h = s * t(n) * e^{\left(\frac{-n*t}{t_{max}}\right)}$. In this function, s is a scaling factor, n is the number of layers and $t_{\max}$ is the position of the maximum response. Following Wierda et al. (2012), these parameters were set to n = 10.1, $t_{\max}$ = 930 and s = 1/1027. The pulse strengths were obtained by optimizing the fit between the estimated signal $x = l * b + i * h$ and the measured pupil dilation signal, where l is the position of each pulse in vector i and b controls for linear drifts in the data. In contrast to Wierda et al., an inter-pulse interval of 50 ms was used in order to increase temporal resolution of the pulses. Furthermore, instead of the Nelder-Mead method we used the Levenberg-Marquardt algorithm (i.e., a non-linear least-squares algorithm) for optimizing the strengths of the attentional pulses. The advantage of the latter is that it is computational cheap and converges to the same unique solution every run, while the Nelder-Mead method yields slightly different outcomes due to randomization, such that it should be repeated multiple times to get a reliable solution.

Local peaks were calculated to determine the latency of the attentional pulses per target. Because there were substantial individual differences in the timing of the pulses, it was difficult to specify a general time window for all individuals that captured the T1 pulse, but did not include the T2 pulse. Therefore, based on the assumption that the first pulse following T1 presentation represents attentional allocation to this target, T1 latency was determined by selecting the first local peak within a time window of -100 to 500 ms. T2 latency was determined as the local peak within a window ranging 400 to 1000 ms for lag 2 and 800 to 1400 ms for lag 6. The amplitude of the pulses was calculated by averaging amplitudes of the local peak with that of the point preceding it and of the point following it.

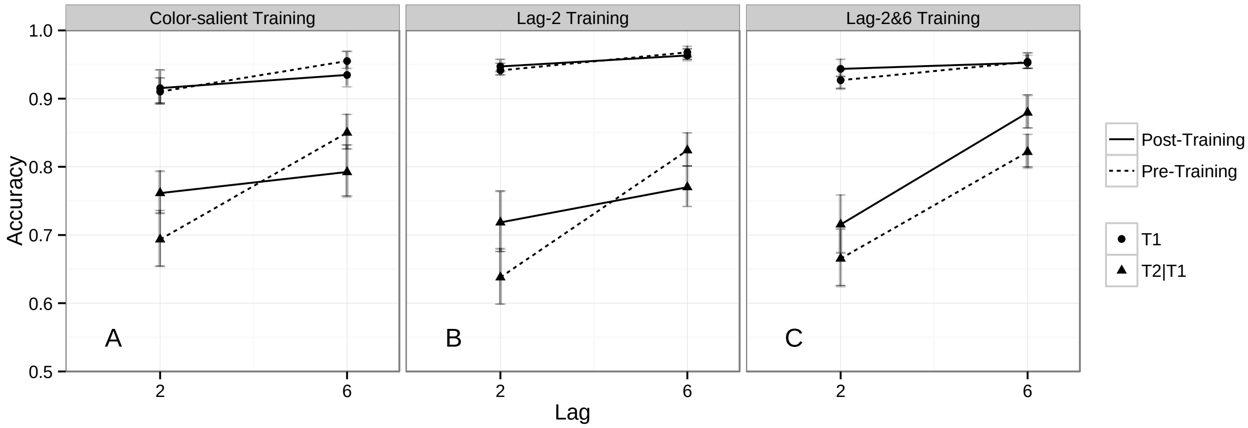

Figure 2: The mean proportion of correct reports of T1 (circles) and T2 given correct report of T1 (triangles) as a function of lag for the pre- (dashed lines) and the post-training block (solid lines) in A) the color-salient condition, B) the lag-2 condition, and C) the lag-2&6 condition. The error bars reflect the standard errors of the mean.

Statistical methods. The latencies and amplitudes of the deconvolved attentional pulses were analyzed using Linear Mixed Models (LMM). Using the *nlme* package (Pinheiro, Bates, DebRoy, Sarkar, & R Development Core team, 2012), we fitted various covariance structures which were compared using the Akaike information criterion (Akaike, 1974). In all cases, either the initial model, which assumes that there are no within-group correlations, fitted best, or the results of the best fitting model did not differ from the initial model. We therefore used the initial model in all subsequent analyses. Expectancy effects in the single-target trials were analyzed by comparing the pulse strength in the pre- and post-training blocks within the same time windows as those that were used to determine T2-related pulses for lag-2 trials and lag-6 trials. A permutation test was performed per time point within these windows. Further statistical methods were similar to those for the behavioral data.

5.2 Results

5.2.1 Behavioral

The mean accuracy for T1 and for T2 given correct report of T1 (T2|T1) in the pre- and the post-training block in all three training conditions is shown in Fig. 2. For T2|T1 accuracy, we performed three behavioral omnibus GLMMs with Lag (2 and 6), Training (pre and post), Condition (Color-Salient, Lag-2, and Lag-2&6), and its two-way and three-way interaction terms as fixed factors. For each model a different training condition served as reference category. A summary of the most important results of these models is presented in Table 1. The results of the full models can be found in the Appendix. We found that the Lag x Training interaction was different both in the Color-Salient condition compared to the Lag-2&6 condition, and in the Lag-2 condition compared to the Lag-2&6 condition. However, there was no evidence that the Lag x Training effect differed between the Color-Salient condition and the Lag-2 condition. As can be seen in Fig. 2, there was a Lag x Training interaction in the Color-Salient condition and in the Lag-2 condition. However, this was not the case in the Lag-2&6 condition. For T1 accuracy, we

Table 1. Summary of omnibus GLMM analysis of T2 accuracy (given T1 correct), with different reference categories. The full models can be found in the Appendix.

Fixed effect	*Estimate*	*SE*	*z-value*	*p-value*
Lag[1] x Training[23]	.86	.19	4.46	< .001***
Lag x Training x Lag-2 Condition[3]	-.05	.26	-.18	.856
Lag x Training[4]	.82	.17	4.71	< .001***
Lag x Training x Lag-2&6 Condition[4]	-1.05	.26	-3.99	< .001***
Lag x Training[5]	-.23	.20	-1.17	.241
Lag x Training x Color-Salient Condition[5]	1.10	.28	3.95	< .001***

Significance codes: '***' < .001, '**' < .01, '*' < .05
[1] Reference category is "lag 6"
[2] Reference category is "pre-training"
[3] Reference category is "Color-Salient condition"
[4] Reference category is "Lag-2 condition"
[5] Reference category is "Lag-2&6 condition"

performed a similar omnibus GLMM, and here we only found an unconditional main effect of Lag (β = -.47, *SE* = .09, *z* = -5.12, *p* < .001). There was neither an overall effect of Training (*p* = .96), nor any interactions between the factors (*p* > .1).

Post-hoc tests revealed that due to the training, in the Color-Salient condition, T2|T1 accuracy improved at the short lag, but decreased at the long lag (*p*s < .004). Furthermore, T2|T1 accuracy was lower at lag 2 than at lag 6 pre-training (*p* < .001), but this difference was not found post-training (*p* = .061). After the Lag-2 training, there also was an increase in T2|T1 performance and a decrease in lag 6 performance (*p*s < .003). Thus, accuracy changed in a similar fashion after the Lag-2 training as after the Color-Salient training. However, after the Lag-2 training, a difference in accuracy between lag 2 and lag 6 remained (*p* < .001). These results suggest that the AB was attenuated after both the Color-Salient training and the Lag-2 training, but not after the Lag-2&6 training (MacLean & Arnell, 2012).

In the training block, mean T1 accuracy was 91.1% (*SE* = 1.6), 96.3% (*SE* = .6), and 95.0% (*SE* = .8) in the Color-Salient condition, the Lag-2 condition, and the Lag-2&6 condition, respectively. At lag 2, mean T2|T1 accuracy in the training block was 83.9% (*SE* = 3.1), 65.9% (*SE* = 3.9), 64.7% (*SE* = 3.4) in the Color-Salient condition, the Lag-2 condition, and the Lag-2&6 condition, respectively. At lag 6 in the Lag-2&6 condition, mean T2|T1 accuracy was 90.4% (*SE* = 1.0) in the training block.

5.2.2 Pupil dilation

In order to study the attentional deployment during the pre- and post-training sessions, the normalized pupil dilation signal was deconvolved to attentional pulses that can be associated with the processing of the targets. These pulses for each training condition are plotted in Fig. 3, 4, and 5. For the T1 analyses concerning all lags, we only took trials into account in which T2 was correctly identified, i.e., no-blink trials. This was motivated by the lack of single-target trials and lag-6 trials where T2 was identified incorrectly, i.e., blink trials. Differences between no-blink trials and blink trials were investigated in separate analyses for lag-2 trials. Furthermore, all

LMMs were modeled with the constraint that T1 was reported correctly, and in the analyses concerning T2 pulses, only trials in which T2 was reported correctly were taken into account.

T1 latency. When analyzing whether Training, Condition, or Training x Condition were predictive factors for T1 latency over all lags (single-target, lag 2, and lag 6), we found no evidence that the effect of Training differed between the Color-Salient training, the Lag-2 training, and the Lag-2&6 training (*p*s > .8). However, there was an unconditional main effect of Training (β = -56.04, *SE* = 12.11, *t* = -4.63, *p* < .001), which indicates that over all conditions the attentional allocation to T1 moved to an earlier time point after the training compared to before the training. In addition, as tested in a separate LMM, T1 latency over all lags could not be predicted by individual mean T1 accuracy (*p* = .80).

For lag-2 trials only, we tested whether T2 accuracy (no-blink trials versus blink trials), Training, Condition, and their two-way interaction terms were predictive for T1 latency. There were no significant interactions (*p* > .1), but, again, there was an unconditional main effect of Training (β = -60.06, *SE* = 16.59, *t* = -3.62, *p* < .001). This indicates that at lag-2 trials, T1 latency shifted to an earlier time point due to the training sessions. The results did not indicate any differences between no-blink and blink trials (*p* = .25). Furthermore, neither AB magnitude (*p* = .35), defined as T2|T1 lag-2 accuracy normalized by T2|T1 lag-6 accuracy, nor mean T1 accuracy (*p* = .13) was predictive for T1 latency at lag-2 trials.

T1 amplitude. The amplitude of the T1 pulse over all lags was analyzed with an LMM with Training, Condition, and its interaction term as fixed factors. This model revealed that the Training effect of the Color-Salient condition was different from the Training effect in the Lag-2&6 condition (β = .09, *SE* = .04, *t* = 2.44, *p* = .015). That is, T1 amplitude increased significantly due to the Lag-2&6 training (β = .07, *SE* = .03, *t* = 2.71, *p* = .007), but was not affected by the Color-Salient training (*p* = .46). However, T1 amplitude did not differ as a result of Training between the Color-Salient condition and the Lag-2 condition, or between the Lag-2 condition and the Lag-2&6 condition (*p*s > .09). Individual mean T1 accuracy was not related to the strength of the T1 pulse (*p* = .95).

For lag-2 trials, we performed an LMM on T1 amplitude with T2 accuracy, Training, Condition, and their two-way interactions as fixed factors. None of the factors interacted significantly with one another (*p* > .1), but overall, whether a trial was a blink trial or a no-blink trial was predictive for T1 amplitude (β = -.07, *SE* = .02, *t* = -3.18, *p* = .002): The strength of the T1 pulse was lower in trials where T2 was identified correctly than in trials where T2 was perceived incorrectly. Finally, we did not find an effect of AB magnitude (*p* = .28) or of mean T1 accuracy (*p* = .51) on T1 amplitude in lag 2 trials.

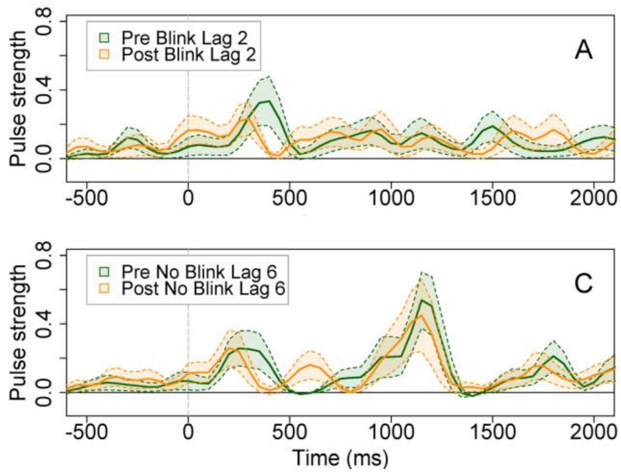

Figure 3: The mean strength of the deconvolved attentional pulses pre- and post-training in the color-salient condition for A) lag-2 blink trials, i.e., T1 reported correctly and T2 reported incorrectly, B) lag-2 no-blink trials, i.e., T1 and T2 reported correctly, C) lag-6 trials, and D) single-target trials. The x-axis is time-locked to the onset of T1 and the depicted signal was smoothed with a Butterworth filter. The error bars reflect the standard errors of the mean.

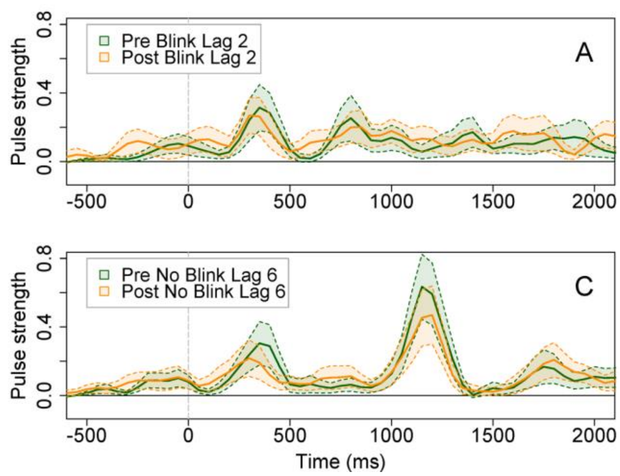

Figure 4: The mean strength of the deconvolved attentional pulses pre- and post-training in the lag-2 condition for A) lag-2 blink trials, i.e., T1 reported correctly and T2 reported incorrectly, B) lag-2 no-blink trials, i.e., T1 and T2 reported correctly, C) lag-6 trials, and D) single-target trials. The x-axis is time-locked to the onset of T1 and the depicted signal was smoothed with a Butterworth filter. The error bars reflect the standard errors of the mean.

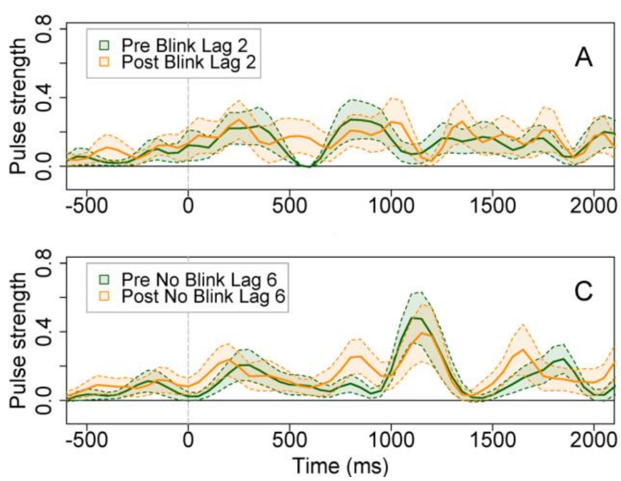

Figure 5: The mean strength of the deconvolved attentional pulses pre- and post-training in the lag-2&6 condition for A) lag-2 blink trials, i.e., T1 reported correctly and T2 reported incorrectly, B) lag-2 no-blink trials, i.e., T1 and T2 reported correctly, C) lag-6 trials, and D) single-target trials. The x-axis is time-locked to the onset of T1 and the depicted signal was smoothed with a Butterworth filter. The error bars reflect the standard errors of the mean.

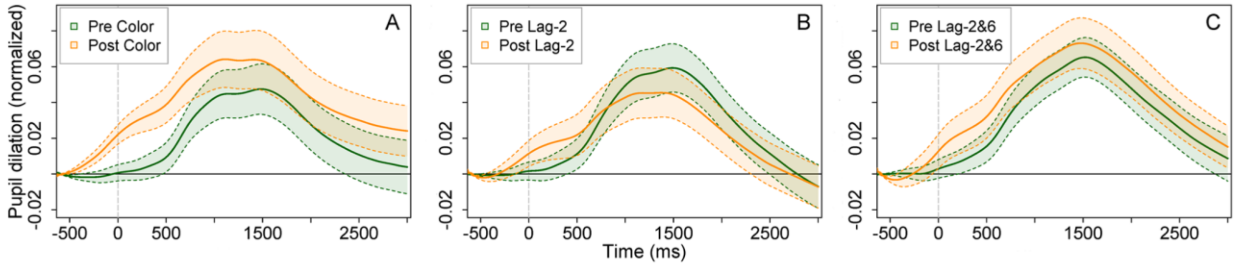

Figure 6: The averaged normalized pupil dilation for the pre- and the post-training block in A) the color-salient condition, B) the lag-2 condition, and C) the lag-2&6 condition. The x-axis is time-locked to the onset of T1 and the error bars reflect the standard errors of the mean.

T2 latency. For T2 lag-2 latency, we tested whether Training, Condition, and Training x Condition were predictive factors. Except for an overall group difference between the Color-Salient condition and the Lag-2&6 condition (β = -73.97, *SE* = 30.11, *t* = -2.46, *p* = .016), which indicates possibly an initial group difference, no effects were found (*p* > .4). However, the timing of the T2 pulse was related to the mean T2|T1 accuracy at lag 2 (β = -122.42, *SE* = 54.19, *t* = -2.26, *p* = .026). Given that we only took trials into account where T2|T1 was identified correctly, this means that even for trials where performance is equal at that particular trial, there is a difference in the timing of attentional allocation which is related to individual, absolute T2|T1 performance. That is, an earlier T2 peak was related to better, absolute T2|T1 performance.

For T2 lag-6 latency, we performed similar LMMs as for T2 lag-2 latency. No effect of Training, Condition, or its interaction term was found (*p* > .1). However, again, the timing of the T2 pulse at lag 6 was related to T2|T1 performance at that particular lag (β = -144.34, *SE* = 67.48, *t* = -2.14, *p* = .034). Thus at lag 6, at trials where T2|T1 performance was correct, an earlier T2 peak can be associated with higher T2|T1 accuracy.

T2 amplitude. With regard to T2 amplitude at lag-2 trials, there were no effects of Training, Condition, or of Training x Condition (*p* > .07). In addition, T2 lag-2 amplitude was not predicted by mean T2|T1 accuracy at that lag (*p* = .57). There were also no effects of Training, Condition, or Training x Condition for T2 lag-6 amplitude. However, T2|T1 accuracy at lag 6 was a marginally significant predictor of T2 lag-6 amplitude (β = .44, *SE* = .23, *t* = 1.95, *p* = .053).

Expectancy effects. In line with previous findings by Wierda et al. (2012), expectancy effects for a second target can be seen in the single target trials as shown in Fig. 3d, 4d, and 5d. To determine whether these expectancy effects for T2 had increased after the training, single-target trials were analyzed, but there was no evidence for enhanced expectancies of the second target after any of the training conditions (*p*s > .08). However, when comparing Fig. 2d, 3d, and 4d visually, post-training enhanced activity around 1300 ms can be seen in the Lag-2&6 condition compared to the Color-Salient condition and the Lag-2 condition. This point lies within the time frame we used to analyze T2 peaks at lag 6. Furthermore, after further visual inspection of the pupil data, we analyzed the time period 400-1000 ms in the lag-6 condition. This is the time window in which expectation effects of a second target at lag-2 might occur. In the Color-

Salient condition, we found a difference at 500 ms (t = -2.14, p = .017), where the activity was higher post-training compared to pre-training. However, in the Lag-2 condition and the Lag-2&6 condition, there were no significant differences (p > .10).

Normalized pupil dilation. Finally, we analyzed the normalized dilation data at the onset of the first target, at which target processing does not yet influence the dilation of the pupil. The results are graphed in Fig. 6. We tested whether Training, Condition, and Training x Condition had an effect on the normalized size of the pupil. This model revealed that in every training condition, the normalized pupil dilation increased significantly as a result of training (Color-Salient: β = .02, SE = .002, t = 14.44, p < .001; Lag-2: β = .001, SE = .002, t = 7.69, p < .001; Lag-2&6: β = .001, SE = .002, t = 7.42, p < .001). This increase was higher in the Color-Salient condition than in both the Lag-2 condition (β = -.01, SE = .002, t = -4.97, p < .001), and the Lag-2&6 condition (β = -.01, SE = .002, t = -4.91, p < .001). The effect of Training did not differ between the Lag-2 and Lag-2&6 condition (p = .98). Furthermore, as tested in a model with AB magnitude, Condition, and AB magnitude x Condition as fixed factors, AB magnitude was a predictive factor for normalized pupil size in the Color-Salient condition (β = -.03, SE = .004, t = -8.97, p < .001) and in the Lag-2 condition (β = -.03, SE = .004, t = -7.08, p < .001), but not in the Lag-2&6 condition (p = .37). The difference between groups was also expressed in the interactions: The effect of AB magnitude differed between the Color-Salient condition and the Lag-2&6 condition (β = .04, SE = .01, t = 4.17, p < .001), and between the Lag-2 condition and the Lag-2&6 condition (β = .04, SE = .01, t = 3.56, p < .001). However, no evidence was found for a different effect of AB magnitude between the Color-Salient condition and the Lag-2 condition (p = .27).

5.3 Discussion

In this study, we aimed to reveal training-induced changes in attentional allocation by measuring pupil dilation during a pre- and post-training AB task. We hoped to resolve the discussion regarding the underlying mechanism of the color-salient training effect as found by Choi et al. (2012). On the one hand, it has been argued that the color-salient training may induce a fundamental improvement in target processing, which may be due to changes in top-down attention or to more efficient processing (Choi et al., 2012). On the other hand, it has been stated that this training may strengthen temporal expectations of the targets, which enhances target perception (Tang et al., 2013). In the current study, in addition to the Color-Salient training condition, we also included two control conditions: the Lag-2 training and the Lag-2&6 training.

In the behavioral data, we found that the AB was eliminated after the Color-Salient training, thus replicating previous findings reported by Choi et al. (2012) and Tang et al. (2013). Surprisingly, however, we showed that training without a salient target, but with a consistent, short target interval, is already sufficient to produce a similar effect. Only when the lag between the targets in the training block was made variable, there was no attenuation of the AB after the training. The deconvolved pupil dilation data showed a shift in the timing of attention allocated to T1 rather than T2. However, this post-training shift was present in all three training conditions. Though expectancies for T2 were visible during single-target trials, they were not modulated by any specific type of training. In all three conditions, the normalized post-training pupil dilation was enhanced prior to target onset compared to pre-training dilation. This increase was largest after the Color-Salient training. Finally, AB magnitude was found to be negatively related to the size of pre-target dilation in the Color-Salient condition and in the Lag-2 condition, but not in the Lag-2&6 condition.

5.3.1 Improvements are lag-specific

In contrast to our hypothesis, we found that training with non-salient, short lag trials can significantly attenuate the AB. This finding implies that the salience of the second target in Choi et al. (2012) may not be a necessary feature. Our findings are in conflict with Choi et al. (2012, experiment 3), who found no effect in a similar non-salient lag-2 training. However, our results may be more reliable, since Choi et al. tested only 6 participants. Furthermore, Choi et al. solely tested whether there was an AB before and after the training, but not whether there was an increase in lag 2 or lag 6 T2 accuracy.

Curiously, in line with Tang et al. (2013), the enhanced performance on lag 2 after the Color-Salient and the Lag-2 training was accompanied by a decreased lag 6 accuracy. This reduced long-lag accuracy was also found in the post-training session on the first of three training days of Choi et al. (2012, Supplementary Fig. 1), but not in their pre-training session on day 2. Crucially, however, on day 2 participants had not only performed the Color-Salient training, but also the post-training session of day 1, which is similar to our Lag-2&6 training. This can explain the combination of an eliminated AB and the lack of decreased lag 6 performance on day 2.

The decreased lag 6 accuracy cannot be explained by generally enhanced processing, since that account would predict an overall, rather than a lag-specific improvement. Instead, the lag-specific changes in accuracy could be the result of temporal expectations that have been induced by the consistent presentation of the short lag in the color-salient training and the Lag-2 training. In line with this explanation, we found an equal increase in lag 2 and lag 6 performance, after both were consistently presented in the Lag 2&6 training. All of this taken together, our behavioral results indicate strongly that training strengthens temporal expectations, even without an explicit cue or a salient target.

In agreement with our results, Visser, Tang, Badcock, and Enns (2014) suggested that participants can make use of temporal consistencies in repeated exposure to a particular lag. However, Visser et al. (2014) argued that these consistencies only benefit performance when participants are explicitly made aware of them. In contrast, our findings suggest that the consistencies can be learned without explicit instructions. Clearly, future research is needed to establish the importance of awareness and motivation in the enhancing effect of temporal expectations.

5.3.2 Change in attentional allocation to T1

In line with the behavioral results, the pupil dilation measurements suggest that the effect of training is not due to an improvement in fundamental processing. We hypothesized that more efficient processing would be reflected in lower amplitudes of target-related peaks after the training. We found that there was no such general amplitude modulation of either T1 or T2, in every training condition. Therefore, it does not seem likely that general, more efficient target processing underlies the training effect. However, overall, we did find lower T1 amplitudes for no-blink trials compared to blink trials. This finding is in line with Wierda et al. (2012), and supports the theory that overinvestment of attention in T1 processing lies at the root of the AB effect (Olivers & Nieuwenhuis, 2005, 2006; Taatgen et al., 2009; Wierda, van Rijn, Taatgen, & Martens, 2010). Thus, the amount of invested attention in processing T1 seems important at trial-level, where it can predict whether the second target will be perceived correctly, but this was not influenced by any of the training conditions.

Choi et al. (2012) suggested that the elimination of the AB after training might be the result of improvements in attentional control. They argued that this would lead to different processing characteristics of T2 within the AB period after training, compared to before training. In the current study, however, we did not find any changes in the allocation of attention towards T2 induced by the color-salient training. That is, both the amplitude and the latency of the attentional T2-pulse were the same before and after the training.

Instead of a change in T2 processing, we found an earlier allocation of attention to T1, irrespective of the type of training. Given that the AB is caused by the effect of T1 processing on a quickly following second target, an early allocation to T1 might reduce the interference between the two targets. In this way, the early attentional allocation to T1 can explain the reduced AB after training. In line with our behavioral results and Tang et al. (2013), the shift in attentional allocation can be the result of increased temporal expectations. That is, the predictable temporal appearance of the targets allows for a more precise attentional allocation to the targets, in such a way that interference is minimized. However, since the earlier T1 allocation was similar in all training conditions, while the behavioral effects were different, we cannot conclude that it underlies the elimination of the AB. Therefore, it seems unlikely that the attenuation of the AB is due to fundamental changes in attentional processing of the targets (Choi et al., 2012).

Enhanced expectations of the first target might also be reflected in the higher level of normalized pupil dilation before the onset of the first target. We found a training-induced increased dilation at this point in all three training conditions. In addition, in the Color-Salient and the Lag-2 condition, we found that the dilation at the onset of the first target was overall related to the AB magnitude, indicating that a high early dilation results in a lower AB. Thus, again, although there are post-training attention-based changes which are related to performance differences, there are no clues that the Color-Salient training or the Lag-2 training, with similar behavioral results, induced different changes than the Lag-2&6 training.

Thus, overall, we found training-induced changes in attentional allocation to T1, irrespective of the training condition. Therefore, we cannot conclude that this shift in T1 allocation underlies the elimination of the AB in the Color-salient and Lag-2 training. It should be noted, however, that we also found an improved short-lag T2 accuracy in every condition. This similarity in behavioral result between the experimental and control conditions makes it difficult to link any change in pupil dilation to changes in T2 accuracy. Future research could control for this, for example, by testing training conditions with decreased temporal consistencies.

5.3.3 Expecting the second target

Although a more precise timing to T1 might be crucial in eliminating the AB, it remains unclear how that would result in decreased accuracy at a longer lag. This decrease indicates that the timing of the second target is also learned during the training. Despite this suggestion, we did not find any training-induced differences in the expectation of the second target in single-target trials. However, a clue that the timing of T2 is indeed learned might be found in the lag-6 trials, which can be seen in Fig. 3c, 4c, and 5c. Here, a post-training increase in activity can be seen in the period in which the short lag second target is expected. However, this increase was only significant in the Color-Salient condition.

A similar expectancy effect can be observed in single-target trials after the Lag-2&6 training. In the timeframe 800-1400 ms (Fig. 3d, 4d, and 5d), the level of activity is stronger in the Lag-2&6 post-training condition than in the Color-Salient condition and the Lag-2 condition. This might be an indication for increased temporal expectations at the time point of the second target at lag 6 in the Lag-2&6 condition. However, within the Lag-2&6 condition, there was no significant increase in activity within this time period. Thus, in spite of the lack of training-induced increased expectancies in the single-target trials, inspection of the graphs does reveal some speculative clues that point towards strengthened temporal expectancies during the training tasks.

5.3.4 The effect of expectations on target detection

In line with Tang et al. (2013), our results suggest that training is modulated by temporal expectations. However, it is still unclear how these expectations change attentional processing. Visser et al. (2014) proposed that the expected onset of the target could be used as a dimension in perceptual filtering. That is, onset might provide further information about the objects that have to be processed, in addition to, for example, form or color. Visser et al. (2014) support this claim by showing that cues about the onset of T2 are more beneficial when target-distractor similarity is high, compared to when similarity is low. According to the authors, this finding implies that temporal expectancies enhance the ability to filter out distractors, thereby enhancing target selection.

As an alternative explanation, however, the consistent presentation of salient short-lag trials may result in a change in the timing of memory consolidation. That is, the color-salient training may promote a memory strategy that is more suitable for the identification of targets in fast succession. In the next section, we will further investigate this hypothesis by introducing a new cognitive model. In the model, the occurrence of the AB depends on the implementation of either a reactive or a proactive working memory strategy.

5.3.5 Summary

In summary, we found that target identification improved at trained lags, even without an explicit cue or a salient target, and diminished at untrained lags. These results suggest that training strengthens temporal expectations. The pupil dilation data showed an earlier attentional allocation to T1, and enhanced normalized pupil dilation prior to T1 onset, after training. Given that these changes occurred irrespective of the type of training, we concluded that the color-salient training does not induce a fundamental change in target processing (Choi et al., 2012). It seems plausible, though, that the shift in timing of allocated attention to T1 was due to enhanced temporal preparation for the first target, which is in line with the temporal expectation theory (Tang et al., 2013). This account was further tentatively evidenced by consistent allocation of attention to expected, but not presented, targets.

6 Cognitive Model

The finding that the AB can be eliminated with just one hour of training implicates that it is unlikely that the AB is the product of structural limitations alone (Experiment 1; Choi et al., 2012). Instead, it seems that people are capable of performing well in the AB task, but employ a suboptimal strategy. Here, we propose a cognitive model that implements such a strategy. The model builds upon the primitive elements theory of cognitive skills (PRIMs) (Taatgen, 2013), which in turn has its foundations in the ACT-R theory (Anderson, 2007). PRIMs proposes that skill learning consist of combining primitive processing elements into larger units. For example: counting requires an iterative strategy, so learning to count leads to the creation of a general iteration strategy. This, in turn, makes it easier to learn other tasks that also require iteration. Thus, the PRIMs model offers an explanation for transfer between tasks that are rather different on the surface: Task-general combinations of primitive elements that are learned in one task can be reused in other tasks. In this way, PRIMs can account for the influence of prior experience on task performance, a factor that is often neglected in models of human behavior.

In our new AB model, executing the AB task consists of a target detection mechanism and a memory consolidation mechanism (Fig. 7). When an item is consolidated in long-term memory (LTM), working memory (WM) is temporarily unavailable for the 200 ms duration of this process. Following Braver, Gray, and Burgess (2007) and Taatgen (2013), two different memory consolidation strategies were implemented. In the *reactive* strategy, the first target is kept in working memory until the second target is detected (Fig. 7a). Then, both targets are consolidated in LTM as one single memory chunk. In the *proactive* strategy, a target is consolidated in LTM immediately after detection (Fig. 7b).

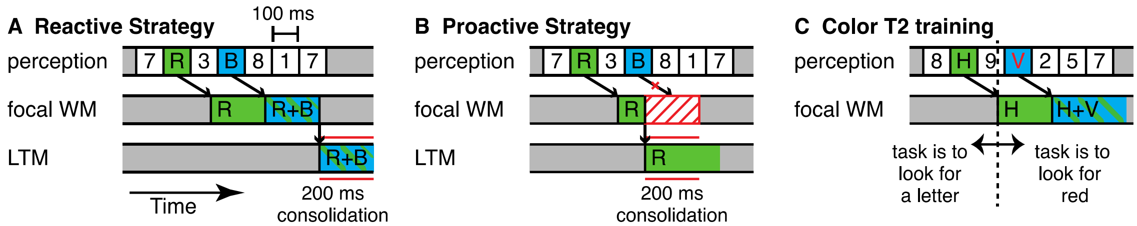

Figure 7: Memory consolidation strategies for the AB. Horizontal lanes represent the passage of time in perception, focal WM and LTM respectively. A) In the reactive strategy, T1 is left in focal WM until T2 is detected, after which they are combined in a single memory chunk that is consolidated in LTM. B) In the proactive strategy, T1 is consolidated immediately after detection, blocking T2 during the 200 ms consolidation period. C) Strategy shift during the color-salient training.

According to the model, the AB is produced by employing the proactive strategy, because memory consolidation of the first target prevents the second target from entering working memory. In contrast, the reactive strategy does not produce an AB, as memory consolidation is postponed until the detection of the second target. Given the extensive literature on the AB, it seems that most people employ the suboptimal, proactive strategy. We propose that this is the case because the proactive strategy is the optimal strategy for other, more common, working memory tasks such as memorizing a list of items. Furthermore, the proactive strategy is simpler than the reactive strategy, as both targets are treated the same way.

The two different strategies of the model can account for the training-induced elimination of the AB found by Choi et al. (2012): The color-salient training enforces a switch from the proactive to the reactive strategy. We propose that the salient T2 in the training triggers a strategy switch: First, the task is to look for a letter target, but once it has been detected the task is to look for a red item (Fig. 7c). This task switch can be explicitly executed, however this may be costly (Monsell, 2003). Instead, it is more efficient to let the task depend on whether there currently is a target in focal working memory. That is, when WM is empty, the task is to look for a letter and when it already contains a letter, the task is to look for a red target. Because this approach demands that the first target is available in WM, it only works with the reactive strategy.

6.1 Methods

We built five models to investigate the effects of different training tasks on AB performance. First, as a control, we tested a model of the AB that implements both the reactive and the proactive strategy. Then, we built a model for the color-salient training of Choi et al., (2012) that uses a reactive strategy to know whether to look for a digit or a red item by checking the contents of focal WM, and a list learning model that is presented with a list of 7 digits which it then needs to recall. In addition, we tested a model that is trained on non-salient lag 2 trials, similar to the Lag-2 training in Experiment 1 and a letter-mask model we will discuss in a moment.

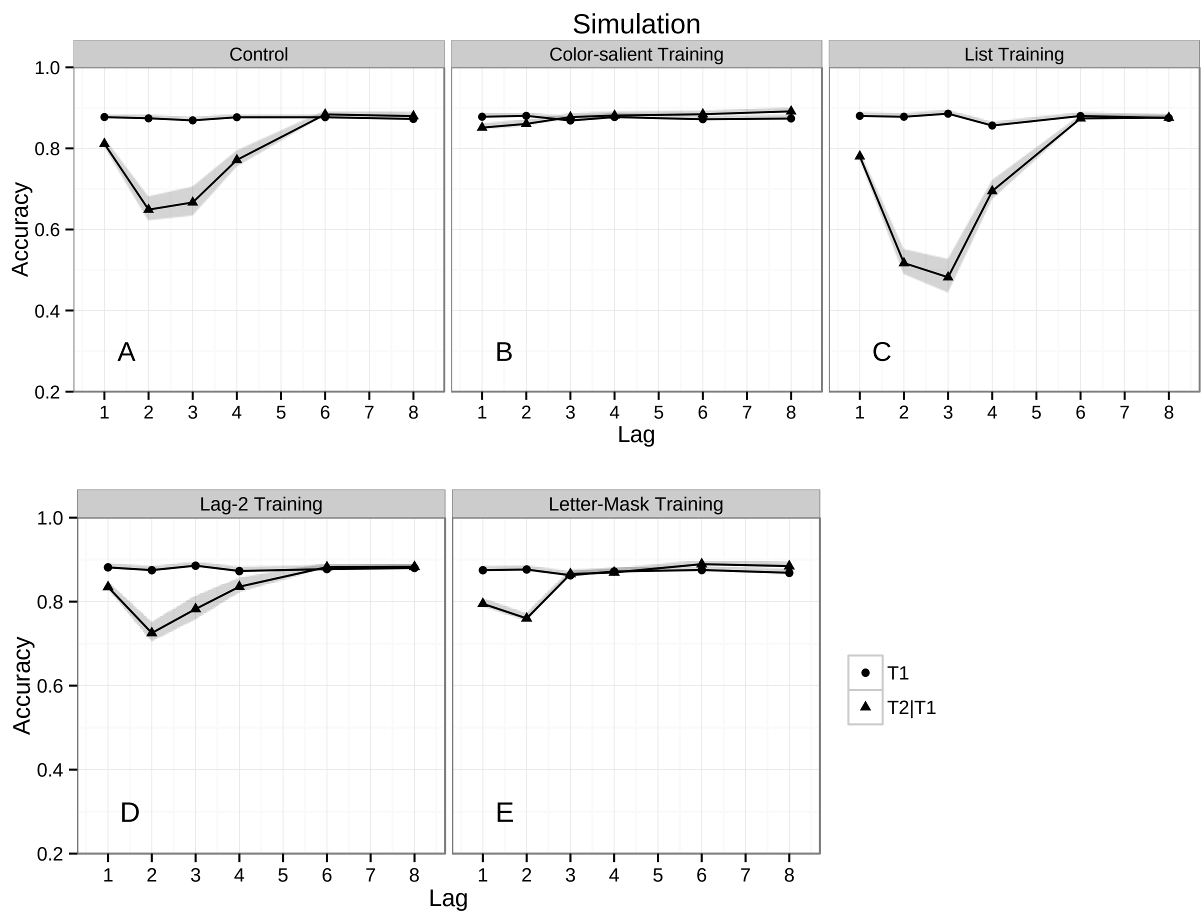

Figure 8: The mean accuracies for T1 (circles) and T2 given correct report of T1 (triangles), in the final 250 trials of simulation, as a function of lag in the A) control condition, B) color-salient training condition, C) list training condition, D) Lag-2 training condition, and E) letter-mask training condition. Grey bands show one standard error.

These models were used in five simulations. In the control simulation, we trained the AB model for 1000 trials (using Lags 1, 2, 3, 4, 6 and 8). In the other four simulations, the model was subjected to 1000 trials of the color-salient training, the list learning task, the Lag-2 training, and the letter-mask training, respectively. The training was followed by 1000 trials of the AB model. Each simulation was repeated 100 times and then averaged.

6.2 Results

Fig. 8 shows the accuracies for T1 and T2|T1 in the final 250 trials of the AB model in the five different simulations. The difference in AB between the simulations is completely attributable to prior training on a different task. In the control condition, the model average shows a modest blink, produced by a mixture of the reactive and the proactive strategy. In the color-salient and list training simulations, however, one of the two strategies dominates. In the case of color-salient training, the reactive strategy is dominant. In line with our behavioral findings and Choi et al. (2012), the color-salient training leads to an absence of an AB. When the model is trained on a list learning task, however, the proactive dominates and produces a stronger AB. Typical human data of the AB resemble those in the list learning condition, indicating that that type of prior knowledge is most representative.

The shift in strategy in the color-salient training model is due to a task switch during the training trials: First, the task is to look for a letter and when one is detected, the task is to look for a red item. Clearly, such a task switch can only occur when the second target is salient. How, then, can the model explain a similar attenuation after the non-salient Lag-2 training in Experiment 1 (Fig. 2b)? Surprisingly, in this model the blink also disappeared (Fig. 8d). The fact that the reactive strategy leads to a higher accuracy during the Lag-2 training appears to be sufficient for the model to favor this strategy over the proactive strategy.

Interestingly, the model predicts that any training task that promotes the use of the reactive strategy should lead to an attenuation of the AB. To test this hypothesis, we designed a new training paradigm. The training consisted of a simple letter-mask task, in which the target letter has to be reported. This task presumably promotes the use of the reactive strategy, because the target needs to be reported immediately: It does not have to be consolidated in LTM. Indeed, after the model was subjected to the letter-mask task, the AB was eliminated (Fig. 8e). To find out whether these model predictions are valid, we investigated the effect of the letter-mask task on the AB of participants. This experiment is presented in the next section.

7 Experiment 2

The PRIMs model of the AB predicts that a letter-mask training attenuates the blink, because it promotes the use of a reactive working memory strategy (Fig. 8e). In the current experiment, we tested the validity of this prediction by subjecting participants to one of three training conditions: The Mask training, in which participants have to report a masked letter; the Speeded Response training, in which participants have to report a letter, which is not masked, as fast as possible; and the Mask & Speeded Response training, in which participants have to report a masked letter as fast as possible. Subjects were trained for 800 trials in each of the conditions. Following the model predictions, we expected the masked condition to be essential for the desired training effect. We hypothesized that a stress on speed might enhance the attenuation of the AB, since it may further discourage consolidation before responding.

7.1 Methods

The experiment consisted of a practice, pre-training, training, and post-training block. The pre- and post-training AB task was similar for all participants. However, participants performed one of three different training tasks: The Mask training, the Speeded Response training, and the Mask & Speeded Response training. Participants could take a break between blocks. The total experiment was completed in approximately 80 minutes.

Seventy-four students (54 female; aged 18-38, mean = 21.5) of the University of Groningen participated in the experiment in return for course credits or a €15 payment. All participants had normal or corrected-to-normal visual acuity. One participant was excluded because he had misunderstood the instructions. After exclusion, 23 participants remained in the Mask training condition, 25 participants in the Speeded Response training condition and 25 participants in the Mask & Speeded Response training condition. The experimental protocol was approved by the Psychology Ethical Committee of the University of Groningen, and participants gave written informed consent prior to the experiment.

The experiment was generated using E-prime 2.0. All displays were presented on a 19-inch computer monitor with a 100 Hz refresh rate. Target stimuli consisted of uppercase consonants (excluding Q, V, and Y) and distractors consisted of single digits (excluding 0 and 1). The items were black, 18-point Courier New and presented on a white background.

AB task. At the start of the experiment, participants performed 25 practice trials. In the pre- and post-training blocks, participants performed 200 trials of a standard AB task. Each trial began with an 850 ms fixation cross, followed by an RSVP of 15 items presented in the middle of the screen at a rate of ~10 Hz.

The first target was always the fourth item in the stream. The second target was pseudo-randomly presented at lag 1, lag 2, lag 3, or lag 8 (each 40 trials) or omitted (40 trials). Stimuli were selected randomly, with the constraint that the same distractor digit was not presented twice in succession, and that the same target was not presented twice within a trial.

Mask Training. The Mask training task consisted of four blocks of 200 trials, preceded by 20 practice trials. Each trial started with a fixation cross. The duration of the fixation cross was randomly chosen from the set 600, 800, 1000, or 1200 ms. After the fixation cross, a target letter was presented followed by a digit mask. The total duration of the target and the mask was always 105 ms. At the start of the first block, the duration of the mask was 36 ms. However, the target-mask ratio was dynamically adapted to the accuracy level of the participant. When the running average accuracy of the participant during a block was lower than 0.75 or higher than 0.85 for more than four trials since the last duration change, the mask duration was decreased or increased by 3 ms respectively.

In order to motivate people to perform well during the training, participants received credits for their performance. When they correctly identified the target, their score was increased with 5 points. For each incorrect response, 5 points were subtracted. After each trial, the trial score and the total score were presented. Participants were told that they would be rewarded with a candy bar when they would reach the target score of 2100 points at the end of the training.

Speeded Response Training. The Speeded Response training was similar to the Mask training, with the additional task to respond as fast as possible. Furthermore, in this condition, the target letter was not followed by a digit mask. Instead, the letter was presented until a response was given. Correct responses faster than the mean reaction time in a given training block where rewarded with 10 points. The target score was 5500 points.

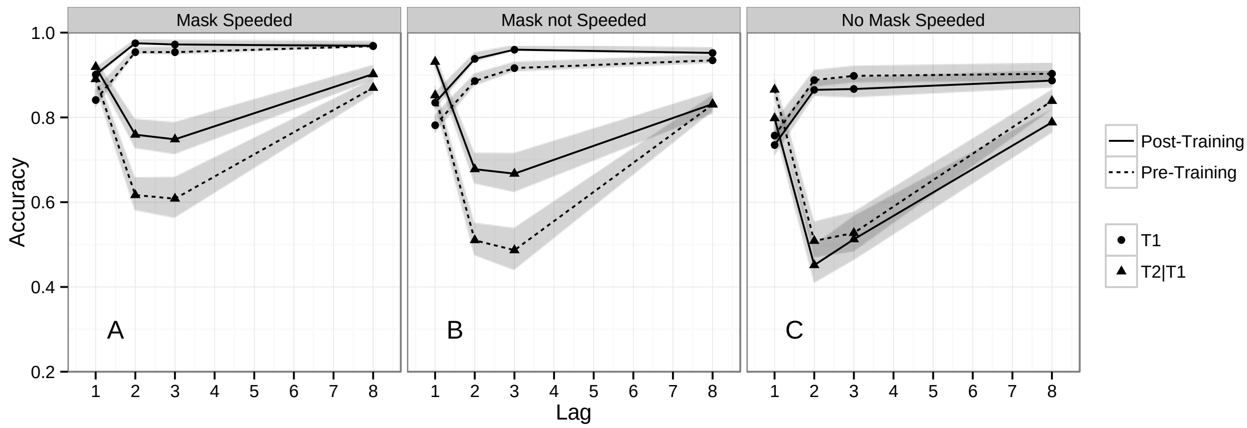

Figure 9: The mean proportion of correct reports of T1 (circles) and T2 given correct report of T1 (triangles) as a function of lag for the pre- (dashed lines) and the post-training block (solid lines) in A) Mask not Speeded condition, B) Mask Speeded condition, and C) the No Mask Speeded condition. Grey bands show one standard error.

Mask & Speeded Response Training. The Mask & Speeded Response training was similar to the Mask training, with the additional task to respond as fast as possible. Correct fast responses were rewarded with 10 points. The target score in this training condition was 4000 points.

7.2 Results

The mean T1 and T2|T1 accuracy in the pre- and the post-training block in all three training conditions are shown in Fig. 9. Order reversals of T1 and T2 were also considered correct. The T2|T1 accuracy data were analyzed with Generalized Linear Mixed Models (GLMM) using the *Lme4* package in R version 3.0.2 (Bates, Maechler, & Bolker, 2012). The results for T2|T1 are given in Table 2. To assess the effect of lag, performance on lags 1 and 8, in which there is typically no AB, was contrasted with lags 2 and 3, in which there typically is an AB. The results show a significant increase in accuracy after the masked training (Training x Mask interaction), which is strongest for the lags typically involved in the AB (Lag x Training x Mask interaction). The speeded manipulation, on the other hand, has no clear effect.

From the results we can conclude that only the mask is effective in reducing the blink, and that the speeded response instruction is not necessary to encourage a reactive memory strategy. This confirms the prediction of the model.

7.3 Discussion

In Experiment 2, we aimed to validate our new PRIMs model of the AB by investigating whether training on a task that promotes a reactive memory strategy attenuates the AB. The model predicted that the letter-mask task reduces the AB by discouraging immediate memory consolidation of the first target (Fig. 8e). We hypothesized that this effect might be enhanced by the stress on speeded response. Confirming the model predictions, we found that training on the

Fixed effect	*Estimate*	*95% CI*	*z-value*	*p-value*
Intercept	2.00	1.80 – 2.20	19.94	<0.001
Lag	-1.78	-1.88 – -1.68	-36.02	<0.001
Training	-0.24	-0.44 – 0.03	-2.28	0.0229
Training x Mask	0.61	0.41 – 0.81	6.05	<0.001
Training x Speeded	-0.11	-0.32 – 0.09	-1.10	0.269
Lag x Training x Mask	0.39	0.23 – 0.55	1.68	<0.001
Lag x Training x Speeded	0.14	-0.02 – 0.55	4.68	0.092

Table 2. Generalized mixed effect model analysis of T2 Accuracy (given T1 correct). The Lag fixed effect contrasts blink lags (2 and 3) with non-blink lags (1 and 8).

letter-mask task significantly reduced the AB. Masking the letter was necessary for improving performance, whereas the speeded response instruction had no effect.

7.3.1 Training induces memory strategy switch

The results show that the AB can be overcome with specific working memory training, even if the training task is dissimilar to the AB task. It thus seems that prior experience plays a major role in the AB: it determines which strategy is employed. When people are trained to consolidate a target immediately after detection, for example through list learning, they will show the AB effect. On the other hand, when they are trained to employ a reactive strategy, they will delay consolidation of the first target and consolidate the two targets as one memory chunk. In this way, they will show a reduced blink. This proposed role of chunking in overcoming the blink is in line with Ferlazzo, Lucido, Di Nocera, Fagioli, and Sdoia (2007), who found that chunking can reduce the AB. In the experiment of Ferlazzo et al. (2007) participants performed an AB task, either with the instruction to report the two digits in a series of letters, or to report the *pair* of digits. The latter instruction resulted in a smaller AB than the instruction to report the separate digits. In terms of our model, the instruction to pair the digits promotes chunking, and thus the reactive strategy.

Although the results of the letter-mask training confirm the model predictions, there are two alternative explanations that we have to consider. First, it is possible the mask training does not induce a change in memory strategy, but generally improves letter perception under masked circumstances. In that case, one might expect that training on a regular AB task would also result in a reduced blink. However, this type of training has so far proven to be ineffective (Braun, 1998; Maki and Padmanabhan, 1994; Taatgen et al., 2008).

As a second alternative explanation, the letter-mask training, like the color-salient training, may induce temporal expectations of the targets (Tang et al., 2013; Visser et al., 2014). Although temporal expectations may be important in overcoming the AB, it is unlikely that they lie at the root of the reduced AB after the letter-mask training. After all, in the Mask training, only one target is presented per trial, and the onset of this target is variable, making it impossible to make use of any temporal consistencies. Furthermore, the lack of a training effect in the Speeded Response training shows that the reduced AB is not due to general task learning in the pre- and post-training blocks.

The PRIMs model of the AB can explain both the effect of the color-salient training and the Lag-2 training: Both tasks promote the use of the reactive strategy. However, while we found that the behavioral effect of the two training tasks is similar (Experiment 1), the model implementation differs. The color-salient training involves a task switch from searching for a letter to detecting a red item, while the consistent presentation of lag 2 trials triggers a reactive strategy just because this strategy is more successful in this task. This different approach might be reflected in the fact that the effect color-salient training has been found more consistently than the effect of non-salient lag-2 training. In addition, it might be reflected in the fact that Visser et al. (2014) only found an improved performance when participants received explicit clues about temporal consistencies. However, future research may point out whether the asymmetrical approach to the color-salient task is necessary for evoking the use of the reactive strategy.

We have shown that promoting the use of the reactive memory strategy leads to an attenuated blink. The other way around, training the model on a list-learning task promotes the proactive strategy, thereby causing a deeper blink than in the control condition. This finding suggests that the AB of participants can also be increased, by presenting them with a task that evokes a proactive strategy. Future studies are needed to verify this prediction.

7.3.2 Generalizability and shortcomings of the model

With regard to the generalizability of the model, it is important to note that the proactive strategy implemented in the model is similar to the previous threated cognition model of the AB (Taatgen et al., 2009). That means that the model can account for a wide range of AB phenomena in the literature, such as Lag 1 sparing (Potter, Chun, Banks, & Muckenhoupt, 1998) and the diminished AB when longer sequences of targets are presented (Di Lollo, 2005). In addition, the model can explain the diminished AB when a secondary task is performed (Taatgen et al., 2009; Olivers and Nieuwenhuis, 2006). In the latter case, the secondary task interferes with the immediate memory consolidation in the proactive strategy, causing it to be delayed. In this way, the model's behavior effectively becomes that of the reactive strategy, leading to a reduction of the AB.

Although the model can account for the enhanced performance on short lags after training, it does not predict the attenuated accuracy at the long lag after the color-salient training (Experiment 1; Tang et al., 2013; Choi et al., 2012 [Supplementary Fig. 1]). That is, in both the reactive and proactive working memory strategy, the model does not predict any interference between the processing of targets when they are sufficiently spaced in time. It thus seems that at least some temporal expectations of the second target are formed through training. Potentially, however outside of the scope of the current thesis, these may be implemented in the model in the following way. After the color-salient training, the reactive strategy is employed; meaning that memory consolidation of the first target is delayed until the second target is perceived. The repeated exposure to short-lag trials in the color-salient training causes one to expect T2 shortly after T1. However, when this expectation is violated in long-lag trials, memory consolidation might be initiated before the second target appears, resulting in a ‘long-lag blink’. Future research may point out whether temporal expectations indeed cause such a delayed memory consolidation of T1 on long-lag trials.

A second issue that has not yet been covered by the model is the role of temporal consistencies in the effectiveness of the color-salient training (Tang et al., 2013). Tang et al. (2013) found that the color-salient training was less effective when the onset of T1 was variable in the post-training AB task. Our model would not predict this effect, since the reactive strategy is independent of the onset of T1. In addition, Tang et al. (2013) found that a variable onset of the color-salient T2 during training was less effective in attenuating the blink. This finding can potentially be explained by the model, since the necessity of a reactive strategy is less salient in this training condition.

7.3.3 Summary

We proposed a new model of the AB, which attributes the AB to a proactive memory strategy. The model shows that the color-salient training and the Lag-2 training encourage the use of a reactive memory strategy, which in turn leads to a reduced AB. Validating the predictions of the model, we found that a simple letter-mask task, that also promotes the reactive strategy, significantly reduced the AB. It remains unclear, however, how a reactive strategy would lead to a diminished accuracy on longer lags.

8 General Discussion

The goal of the current thesis was to investigate how it is possible that the AB can be overcome through training. On the one hand, it has been argued that color-salient training causes fundamental processing or attention-based improvements (Choi et al., 2012). On the other hand, Tang et al. (2013) stated that the eliminated AB is the result of increased temporal expectations, which are triggered by temporal consistencies in the task.

In Experiment 1, we measured pupil dilation during a regular AB task before and after three different training tasks: the color-salient training of Choi et al. (2012), a training in which only non-salient lag 2 trials were presented and a training in which both non-salient lag 2 and lag 6 trials were presented. We found that the AB was eliminated after both the color-salient and the Lag-2 training. Consistent with the temporal expectations hypothesis (Tang et al., 2013), we found that target identification was improved at the trained lags, while it was diminished at untrained lags. Although the results of the deconvoluted pupil dilation were less straightforward, we found evidence that training mainly affected the timing of attentional allocation towards T1. Importantly, we found no evidence for improved general target processing. That is, none of the training conditions led to a decreased amplitude of target-related pulses.

Next, we presented a model based on PRIMs (Taatgen, 2013) which explains the eliminated AB after the color-salient training (Choi et al., 2012) and the Lag-2 training (Experiment 1) through a switch in memory strategy. The model shows that the proactive memory strategy results in the regular blink, whereas the reactive strategy does not. The model predicts that training on a task that promotes the reactive memory strategy will decrease the AB. In Experiment 2 we confirmed this prediction by showing that training on a letter-mask task reduces the AB.

8.1 Overcoming the blink

Overall, our results suggest that the effects of training on the AB are not due to fundamental improvements in processing limitations. Instead, we showed that the improved ability to detect targets in fast temporal succession after the Color-Salient training, the Lag-2 training and the letter-mask training can be successfully modeled by a switch from a proactive to a reactive memory strategy. Our model suggests that the AB eventually arises because working memory is temporarily unavailable during memory consolidation of the first target, but that the limiting effect of this mechanism can easily be bypassed by employing a strategy in which consolidation is delayed.

However, a shortcoming of the current model is that a reactive strategy does not lead to the decreased long-lag accuracy after the Color-Salient and Lag-2 training (Experiment 1; Tang et al., 2013). It therefore seems that, in addition to a switch in memory strategy, temporal expectations play an important role in the elimination of the AB after the color-salient training (Tang et al., 2013). That is, when two targets are presented with a predictable onset, people are able to use this predictability. In this thesis, we have found several clues that this is indeed the case. First, the deconvolved pupil dilation shows that training might induce earlier attentional allocation towards T1. Building on theories that suggest that the AB arises from the interference between T1 and T2 processing (Lagroix, Spalek, Wyble, Jannati, & Di Lollo, 2012), earlier T1 processing might minimize this interference. Second, after the Lag-2, Lag-2&6, and to a greater extent after the Color-Salient training, we found a higher normalized pupil dilation before the presentation of T1, indicating an increased anticipation of this presentation. Third, we found increased temporal expectations of the short-lag second target in lag-6 trials after the Color-Salient training. It has to be noted, however, that no further increased expectation effects were found. Overall, temporal expectations seem to play an important role in the training effect after the Color-Salient training, the Lag-2 training and the Lag-2&6 training. Importantly, however, they cannot explain the reduced AB after the letter-mask training.

Thus, in short, the effect of training on the AB can be explained by a change in memory strategy and temporal expectations. These two training-induced changes in task-approach are not mutually exclusive. That is, temporal expectations may be important in switching memory strategy: when one knows that two targets are presented in fast succession, it is more likely that one will discover that a reactive memory strategy is optimal. The other way around, the reactive memory strategy relies on the anticipation of a second target, so that it can be consolidated together with the first target.

In this thesis, we have shown that a memory strategy acquired in a training task (e.g. the color-salient training, the list learning task, the letter-mask training) can be transferred to a different task (e.g. the regular AB-task). An issue that still needs to be established is the conditions under which learned strategies will be applied. For example, will training on a letter-mask task also improve performance on an AB task with pictures (Evans & Treisman, 2005) or words (Barnard, Scott, Taylor, May, & Knightley, 2004)? The PRIMs model might prove valuable in resolving this issue. PRIMs predicts that transfer of strategies and skills is possible between tasks that are quite different on the surface, but share the same underlying structure (Taatgen, 2013). For example, PRIMs successfully modeled the transfer of a proactive strategy from a complex working memory task to a Stroop task (Chein & Morrison, 2010; Taatgen, 2013).

We have suggested that temporal expectations might aid target detection in two ways. First, by inducing a reactive memory strategy and second, by enforcing an earlier allocation of attention to T1, thereby decreasing interference between the processing of T1 and T2. As an alternative explanation, however, the expected onset of the targets can be used as a dimension upon which a perceptual filter is based (Visser et al., 2014, Martens & Johnson, 2005). More research is needed to establish the influence of temporal expectations on perception, and the conditions under which expectations are formed.

8.2 Implications for theories of the AB

Although the current thesis is focused on the effects of training on the AB, the presented results also have implications for theories on the AB itself. The effects of training on the AB presented here deliver further evidence against theories explaining the AB solely as the product of resource limitation (e.g. Chun & Potter, 1995; Jolicœur & Dell'Acqua, 1998; Dehaene, Sergent, & Changeux, 2003). Instead, the results, as well as our PRIMs model of the AB, once more suggest that the AB reflects a failure in attentional control (Nieuwenstein et al., 2005; Olivers et al., 2007; Taatgen et al., 2009; Wyble et al., 2009).

Importantly, however, future models of the AB should account for the effects of training on the AB presented here and in other studies (Choi et al., 2012; Tang et al., 2013; Visser et al., 2014). Whereas fundamental limitations of the cognitive system might be essential in explaining the blink (such as the 200 ms memory consolidation period in our model), models of the AB should explain how such limitations are circumvented. Our model, and the PRIMS model in general, might be key in uncovering the interaction between strategy and cognitive limitations.

8.3 Implications for theories in psychology

Our new PRIMs model of the AB shows that, in general, we have to be careful to assign suboptimal performance in any psychological paradigm to structural limitations. Strategies that are based on prior experience, or that are triggered by the instructions of the task, should be taken into consideration. Again, this does not mean that limitations of the cognitive system do not play a role. After all, in our model the AB is caused by the 200 ms memory consolidation during which working memory is unavailable. The PRIMs model might prove valuable in investigating the distinct contribution of prior experience and strategy to behavior.

9 Conclusions

In this thesis, we have demonstrated that a training task without a salient target, but with a consistent inter-target interval, can reduce the AB. Furthermore, our results suggest that temporal expectations of the onset of trained targets are formed during training. Our new model shows that temporal consistencies can eliminate the AB by enforcing a shift from a proactive to a reactive memory strategy. Together, our findings suggest that the training effect is not due to improvements in fundamental processing limitations, but in strategic control of attention. Therefore, the AB phenomenon should not be seen as the product of structural limitations, but instead as the consequence of a suboptimal attention strategy.

10 References

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11 Appendix

Table 1a. Results omnibus GLMM behavioral results with the color-salient condition as reference category

Fixed effect	*Estimate*	*SE*	*z-value*	*p-value*
Intercept	2.01	.20	10.11	< .001***
Lag[1]	-1.12	.14	-8.00	< .001***
Training[2]	-.43	.15	-2.90	.004**
Lag-2 Condition[3]	-.18	.27	-.66	.510
Lag-2&6 Condition[3]	-.19	.28	-.66	.510
Lag x Training	.86	.19	4.46	< .001***
Lag x Lag-2 Condition	-.11	.19	-.57	.567
Lag x Lag-2&6Condition	.09	.19	.48	.632
Training x Lag-2 Condition	.03	.20	.14	.891
Training x Lag-2&6 Condition	.91	.22	4.25	< .001***
Lag x Training x Lag-2 Condition	-.05	.26	-.18	.856
Lag x Training x Lag-2&6 Condition	-1.10	.28	-3.96	< .001***

Significance codes: ‘***’ < .001, ‘**’ < .01, ‘*’ < .05
[1] Reference category is “lag 6”
[2] Reference category is “pre-training”
[3] Reference category is “Color-Salient condition”

Table 1b. Results omnibus GLMM behavioral results with the lag-2 condition as reference category

Fixed effect	*Estimate*	*SE*	*z-value*	*p-value*
Intercept	1.83	.18	9.91	< .001***
Lag[1]	-1.22	.13	-9.78	< .001***
Training[2]	-.40	.13	-3.03	.003**
Color-Salient Condition[3]	.18	.27	.66	.510
Lag-2&6 Condition[3]	-.01	.27	-.02	.982
Lag x Training	.82	.17	4.71	< .001***
Lag x Color-Salient Condition	.11	.19	.57	.567
Lag x Lag-2&6 Condition	.20	.18	1.10	.274
Training x Color-Salient Condition	-.03	.20	-.14	.891
Training x Lag-2&6 Condition	.89	.21	4.33	< .001***
Lag x Training x Color-Salient Condition	.05	.26	.18	.856
Lag x Training x Lag-2&6 Condition	-1.05	.26	-3.99	< .001***

Significance codes: ‘***’ < .001, ‘**’ < .01, ‘*’ < .05
[1] Reference category is “lag 6”
[2] Reference category is “pre-training”
[3] Reference category is “Lag-2 condition”

Table 1c. Results omnibus GLMM behavioral results with the lag-2&6 condition as reference category

Fixed effect	*Estimate*	*SE*	*z-value*	*p-value*
Intercept	1.82	.20	9.40	< .001***
Lag[1]	-1.02	.13	-7.73	< .001***
Training[2]	.49	.16	3.11	.002**
Color-Salient Condition[3]	.19	.28	.66	.510
Lag-2 Condition[3]	.01	.27	.02	.982
Lag x Training	-.23	.20	-1.17	.241
Lag x Color-Salient Condition	-.09	.19	-.48	.632
Lag x Lag-2 Condition	-.20	.18	-1.10	.274
Training x Color-Salient Condition	-.92	.21	-4.25	< .001***
Training x Lag-2 Condition	-.89	.21	-4.33	< .001***
Lag x Training x Color-Salient Condition	1.10	.28	3.95	< .001***
Lag x Training x Lag-2 Condition	1.05	.26	3.99	< .001***

Significance codes: '***' < .001, '**' < .01, '*' < .05

[1] Reference category is "lag 6"

[2] Reference category is "pre-training"

[3] Reference category is "Lag-2&6 condition"