Atten Percept Psychophys (2017) 79:2257–2274
DOI 10.3758/s13414-017-1391-9

Training and the attentional blink: Raising the ceiling does not remove the limits

James T. Enns [1,2] · Paul Kealong [1] · Jennifer G. Tichon [3] · Troy A. W. Visser [2]

Published online: 24 July 2017

Abstract The attentional blink (AB) is a widely studied deficit in reporting the second of two sequentially presented targets when they occur within 500 milliseconds. The AB often is interpreted to index a structural limit in sequential visual processing. However, this interpretation is challenged by reports that the deficit can be reduced with several hundred trials of specific training (Braun in *Nature, 393*(6684), 424–425, 1998; Choi et al. in Proceedings of the National Academy of Sciences*, 109*(30), 12242–12247, 2012; Taatgen et al. in *Cognitive Psychology, 59*(1), 1–29, 2009) and other reports that some individuals experience very little or no deficit, even without specific training (Martens et al. in *Journal of Cognitive Neuroscience, 18*(9), 1423-1438, 2006). Yet neither of these claims has been studied when the artifact of ceiling effects has been removed. We sent a small number of participants (n = 5) home to practice an AB task on their mobile phones for 3,000-6,000 trials (Experiment 1) and trained a much larger number of participants (n = 48) in a similar way for 1,200-1,800 trials (Experiment 2). Both experiments used adaptive procedures to equate task difficulty throughout training to keep second-target accuracy below ceiling levels. The results showed strong training effects on the rate of processing sequential information. Despite this, there were (a) robust AB effects after training for most participants, (b) no benefit for training on difficult versus easy target tasks, and (c) substantial correlations between the magnitude of the AB before and after extensive training. These findings support the interpretation that the AB is an index of a structural limit in the ability to consciously process rapid visual sequences.

Keywords Attentional blink · Attention in learning · Dual-task performance

Public Significance Statement The attentional blink is among the most widely studied tasks in human attention. We asked a deceptively simple question: Can the attentional blink be eliminated with extensive training? This has not received a satisfactory answer to date, because previous studies have not avoided ceiling effects. Here we do so with an adaptive procedure as participants undergo hundreds of training trials on an attentional blink app installed on their smartphones. While training increases the rate at which rapid sequential information can be processed, it does not remove the second target deficit, which is the hallmark of the attentional blink.

✉ James T. Enns
jenns@psych.ubc.ca

[1] Department of Psychology, University of British Columbia, 2136 West Mall, Vancouver, BC, Canada V6T 1Z4

[2] School of Psychological Science, University of Western Australia, Crawley, Australia

[3] Griffith Institute for Educational Research, Griffith University, Mt Gravatt, Australia

Since the introduction of the attentional blink (AB) task and its main finding—that the second of two sequentially presented targets is selectively disadvantaged when the targets appear within 500 milliseconds of one another (Raymond, Shapiro, & Arnell, 1992)—the dominant interpretation has been that that the AB arises from structural limitations in sequential object processing (Dell'Acqua, Dux, Wyble, & Jolicœur, 2012; Goodbourn et al., 2016). Admittedly, there have been strong differences of opinion on what that limitation may be. Theoretical ideas have ranged from the proposal of a bottleneck in the late-stages of object identification (Chun & Potter, 1995; Jolicœur & Dell'Acqua, 1998), to competition between the items currently in visual short term memory (Raymond et al., 1992, 1995, Raymond, Shapiro, & Arnell, 1995), to a temporary loss of cognitive control in maintaining a search template for the target (Di Lollo, Kawahara, Ghorashi, & Enns, 2005; Taatgen, Juvina, Schipper, Borst, &

Martens, 2009), to an inhibition of target processing triggered by the appearance of inter-target distractors (Olivers & Meeter, 2008), to the activation of an episodic memory trace for the target item (Bowman & Wyble, 2007; Wyble, Bowman, & Nieuwenstein, 2009). Despite their differences, these theories all agree that the limitation is structural, meaning that it reflects a fundamental feature of visual cognitive processing and not merely the consequence of limited skill and experience in the performance of a specific laboratory task.

This interpretation is challenged by two classes of findings. One is the apparent elimination of an AB with training (Braun, 1998, Choi, Chang, Shibata, Sasaki, & Watanabe, 2012; Taatgen et al., 2009). The second is the apparent existence of a small number of individuals for whom the AB task poses no measureable challenges (Martens, Munneke, Smid, & Johnson, 2006; Martens & Valchev, 2009). In the present study, we considered both of these findings in light of the concern that they may have been reported without sufficient care taken to eliminate the well-known measurement artifact of ceiling effects. Without eliminating ceiling effects, both the question of the role of training and the question of whether some individuals are immune to the AB has not been answered fully. Before describing our approach to this question, we briefly recap the previous literature in these two areas.

The question of whether training can eliminate the AB began with Maki and Padmanabhan (1994), who reported that the AB was almost entirely eliminated with 10 days of training on a specific variant of the task. However, the AB was readily reinstated following training if the target features that had been learned in the task were introduced into the distractor set. The authors interpreted these findings to support the idea that the AB reflects a competition between items currently loaded into visual short term memory (Raymond et al., 1992). With training, participants became better at suppressing nontarget features, although when the features to be suppressed were shared with the target features, the competition in short-term memory was reinstated.

A few years later, Braun (1998) reported training differences on an AB task requiring identification of a centrally presented target (T1) that was followed by a pop-out visual search task containing the second target (T2). While novices showed a robust AB on the visual search task, individuals who had previously undergone 2,500 trials of training on a different AB task, and individuals who routinely did AB tasks in the lab (e.g., the authors and their close colleagues) did not experience the AB on the visual search task. Even researchers that have examined the magnitude of the AB after several hundred trials have noted the AB often is diminished with training. For example, Taatgen et al. (2009) reported that there was a significant reduction in the AB over time, even when the training only involved 4 blocks of 112 trials.

Perhaps the most dramatic claim of a training effect on the AB was the report form Choi et al. (2012) that the AB could be eliminated entirely with a 3-day training regime that involved giving participants an aid to second-target identification by presenting the second target in a color that was distinctive from the rest of the stream items. After training with these supports, the AB was eliminated even when participants identified targets in a stream in which all the items were now the same color. These authors also reported control experiments to show that the benefit of training with the salient-colored second target only occurred when the unique color was spatiotemporally correlated with the target. However, Tang, Badcock, and Visser (2014) questioned this interpretation. These authors considered the alternative hypothesis that the role of the unique item in training was to create temporal expectations about when targets would appear. In this view, the structural limitation had not been overcome, but rather participants had learned to use a temporal cue to change expectations about *when* targets would appear. To support this interpretation, Tang et al. (2014) replicated the method of Choi et al. (2012) and extended it in several ways. In a critical experiment, they showed that when the temporal variability of the second target was reinstated either during the training or in post-test assessment, there was still a robust AB. This was consistent with participants' acquiring specific temporal expectations during the training phase, rather than overcoming structural processing limits.

The second literature challenging the AB as reflective of a structural limitation concerns a small number of individuals who appear to be immune from the second target deficit. Martens et al. (2006) estimates that approximately 5% of participants in a typical university undergraduate population experience an AB that is 10% or less of the magnitude typically reported. Moreover, these rare individuals ("non-blinkers") performed robustly better than their peers when tested on a wide range of stream rates (i.e., from 10 Hz to 20 Hz; Martens et al., 2006) and were less influenced than their peers by additional distracting information in the stimulus displays (Martens & Valchev, 2009).

It is safe to say that ceiling effects have not been avoided in both of the literatures in which the AB has been reported to vanish. By definition, training studies attempt to increase accuracy for the second target to the high baseline levels of accuracy enjoyed by the first target. Studies of nonblinkers suffer from the same measurement ambiguity (Martens et al., 2006; Martens & Valchev, 2009), as they search for individuals who perform at ceiling levels with a minimal T2 deficit. Thus, in both literatures, it is unclear whether the AB has indeed vanished, or whether measures lack sufficient sensitivity to detect deficits that are still present.

To address this question, our approach was to remove ceiling effects by making adaptive adjustments to keep second target accuracy within a measureable range, even after extensive training. In Experiment 1, we did this by reducing the interval between T2 and its subsequent mask when T2 accuracy was too high, which has long been known to reduce second target accuracy (Brehaut, Enns, & Di Lollo, 1999; Giesbrecht & Di Lollo, 1998). Because this manipulation was not enough to eliminate a ceiling effect in all participants, in Experiment 2 we added further manipulations to reduce T2 accuracy, reducing the duration of all rapid-serial visual presentation (RSVP) stream items ("on time") and the interval between stream items ("off time"), when T2 accuracy was near ceiling (Kawahara & Enns, 2009; Taatgen et al., 2009). These three stream parameters were adjusted in a hierarchical way if accuracy remained high, that is, by reducing the T2-mask interval first, followed by reductions in on time, and then reductions in off time. If accuracy was too low, these parameters were increased following the same hierarchical sequence. The rationale behind using these variables to reduce second target accuracy during training was that they would leave the overall task as similar as possible to the conventional AB task, while ensuring that second target accuracy remained in a measurable range.

We reasoned that if the AB is a consequence of structural limits on rapid sequential processing, then it should persist in the face of extensive training, provided that accuracy remains in a measurable range throughout the training period. This outcome would be consistent with there being a hard structural limit on sequential information processing, along the lines of Goodbourn et al. (2016) and Joseph, Chun, and Nakayama (1998, pp. 425), who claimed that "all visual information is required to pass through a limited-capacity stage before it can be explicitly detected." Alternatively, if the limitations reflected in the AB can be ameliorated with training, then training on the AB task should eliminate the second target deficit, even when overall T2 accuracy remains in a measurable range. This would be consistent with some aspects of the two-target identification task becoming automated or habitual through training (Awh et al., 2004).

Experiment 1

Experiment 1 was exploratory, because we did not know how rapidly training might proceed or how effective it would be after implementing an adaptive procedure. As such, we opted for very extensive training with a small number of participants. We also used participant's personal smartphones to deliver the testing and training tasks. This meant that participant could train in their spare time and on their own schedule, accumulating reimbursement that was contingent on the number of trials they completed. Based on the information that we acquired in this first experiment, we then opted for a procedure focused on the first 1,500 trials of training with a larger contingent of participants in Experiment 2.

Method

Participants Five adult volunteers (3 males, 2 females; 22–27 years, median = 23.5 years) with normal or corrected-to- normal visual acuity participated in the study. All were university students who received remuneration of $1 for every block of 60 trials completed and provided informed consent prior to testing. The procedure was approved by the Behavioral Research Ethics Board at the University of British Columbia and was in accordance with guidelines of the American Psychological Association and the Declaration of Helsinki.

Apparatus, stimuli, and procedure The attentional blink task was presented on the personal smartphones of the participants, using an application written in the Unity Language for both Android and Apple phones (Don't Blink). The native temporal resolution of these devices is 60 Hz, so the program was designed for individual presentation frames of 16.67 milliseconds in duration. Individual phones varied somewhat in their screen characteristics, with Android phones having LCD or AMOLED screens of 1920 x 1080 pixels (Samsung S5, HTC one M8, Nexus 5) and Apple phones having an LCD screen of 1136 x 640 pixels (iPhone 5S).

Figure 1a shows the introductory screen of the program. Selecting "Start a block" advances to a screen with a central plus sign (Fig. 1b). Tapping anywhere on that screen with a finger initiates one trial (Fig. 2a). Each trial included two letter targets (T1, T2) and their respective masks, embedded within a stream of digits. Following each stream, a response panel appears (Fig. 1c), allowing participants to enter two target letters. Following the completion of one block, a feedback screen is presented (Fig. 1d) indicating the mean accuracy achieved on the second target in that block. Selecting the "Statistics" option in Fig. 1a leads to the screen shown in Fig. 1e, where the number of blocks completed so far is indicated, along with the overall mean accuracy on the second target for the entire experiment.

Figure 2a illustrates the sequence of events on a single trial. Stream items were presented initially for two frames (on time = 33.33 milliseconds) followed by four blank frames (off time = 66.67 milliseconds) in order to present a new stream item every 100 milliseconds. This meant the stream rate began with the typical 10 Hz used in the vast majority of attentional blink studies. After 1-8 leading digits, selected randomly and equally often, T1 and its mask was presented, followed by 1, 3, 5, or 7 intervening digits also randomly presented, and then T2 and its mask was presented to end the stream. The digits included 2 through 9; the target letters used were all the uppercase English letters except for I, O, P, Q, and Z, because they were confusable with other digits and letters. The mask following each target was one of four randomly chosen keyboard symbols (@, #, &, %). These stream items were presented as png files that were each 400 x 400 pixels in size. For a phone with

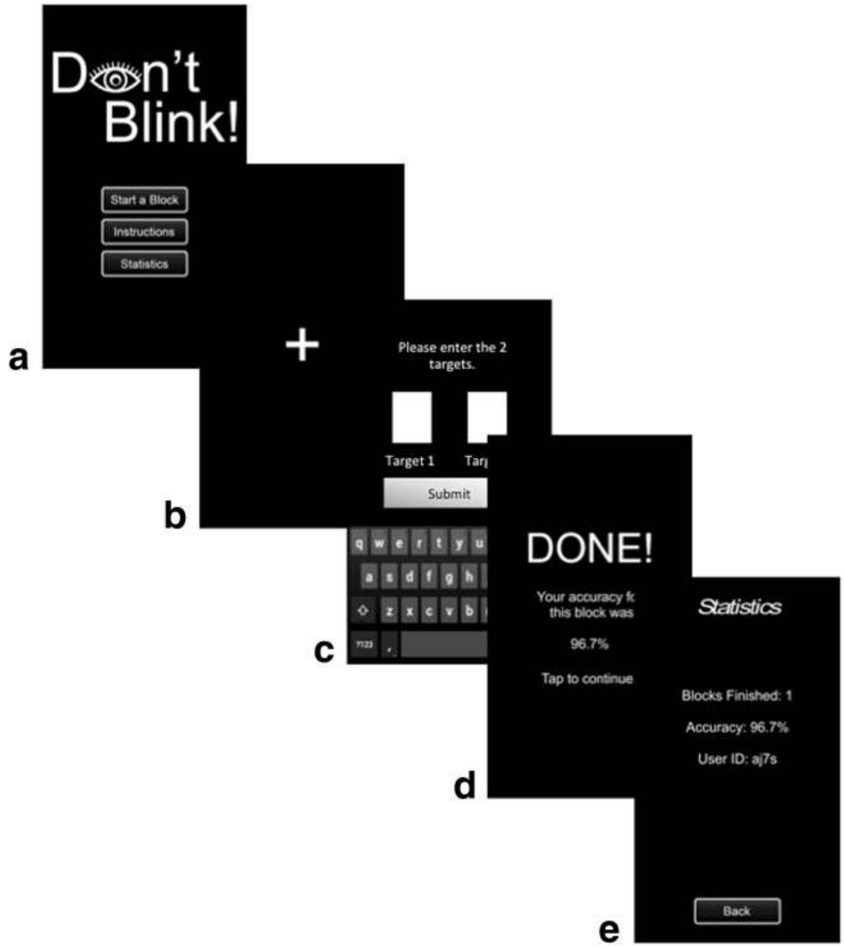

Figure 1 Main screens on the smartphone application developed to train participants in the attentional blink task. (**a**) Introductory screen, (**b**) stream initiation screen, (**c**) response screen, (**d**) block summary screen, and (**e**) experiment summary screen

a screen of 1,136 x 640 pixels that meant the items occupied approximately 1.81 degrees of visual angle when held at a typical phone viewing distance of 40 centimeters.

An adaptive procedure was used to adjust the T2-mask interval following each block of trials. If mean accuracy of T2 in a preceding block was greater than 80%, the T2-mask interval was reduced by 1 frame for the next block. Likewise, if T2 accuracy was less than 60%, then the T2-mask interval was increased by 1 frame. Thus, T2-mask interval was varied contingently on the participant's T2 accuracy from 4 frames (default) to 0 frames (if the participant was able to maintain accuracy within 60-80% correct).

Participants were told in the initial meeting about the "second target deficit" (attentional blink) that occurs for most people when trying to identify two targets in a rapid sequence. They also were told that the goal of the experiment was to see if they could improve their second target accuracy over time with training. They were encouraged to train in their spare time, for a period of 1 week, before returning to the lab to have their data downloaded by the experimenter and to be remunerated for their efforts. The rules of participation included an agreement to train for at least 50 blocks during the course of 1 week and not more than 100 blocks (3000-6000 trials in total). Before leaving the initial meeting, each participant completed at least one block of trials to ensure that they understood the task, as well as other features of the app, including feedback.

Results

The results showed that training was very effective in reducing the T2-mask interval from 4 frames (68 milliseconds) to an average of less than 1 frame (17 milliseconds) for the five participants, while they maintained a T2 report accuracy of 60% to 80%. Furthermore, the vast majority of this training benefit occurred with 20-30 blocks (1200-1800 trials). The main finding of the experiment was that these substantial training benefits in identifying targets in rapid streams did not translate into the elimination of the attentional blink. T2 accuracy was still significantly below T1 accuracy, especially at the shorter lags, for the participants as a group, although two of the participants managed to achieve a negligible T1-T2

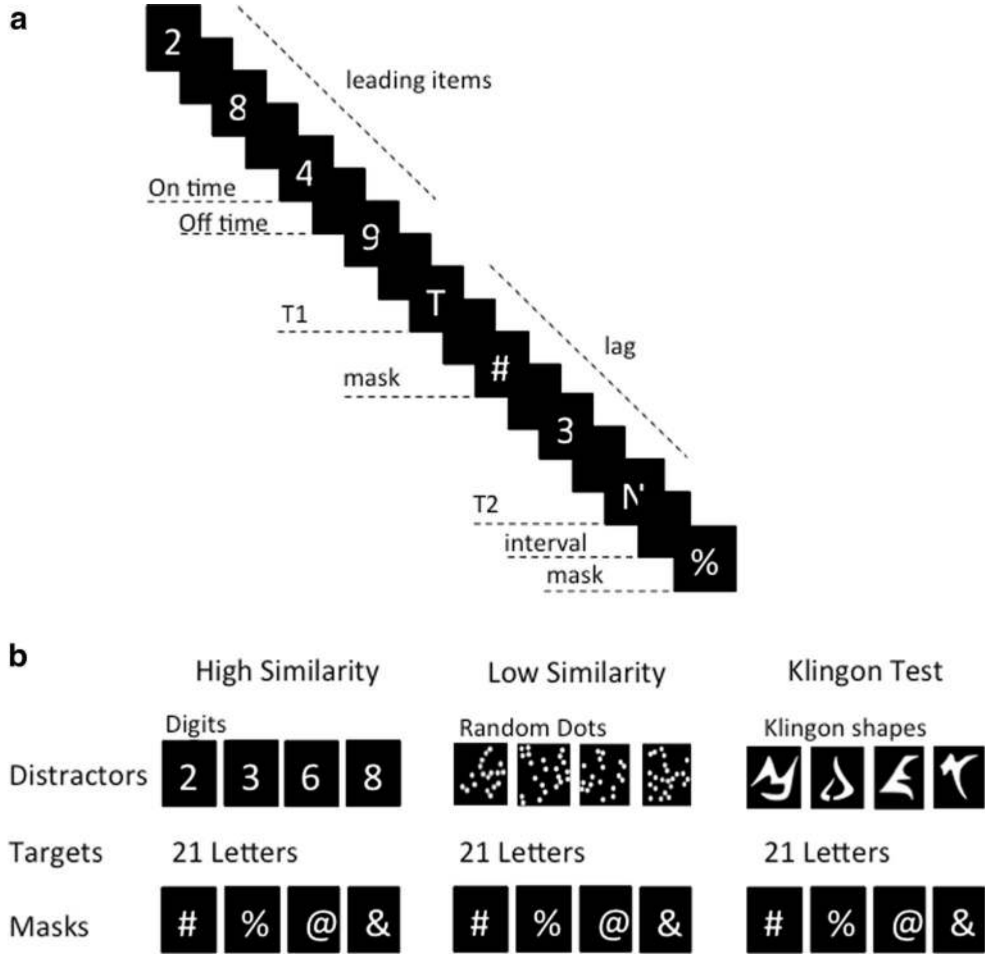

Figure 2 Target identification task within the rapid serial stream of items. (**a**) 6-10 leading digits were followed by a first target (T1) and a mask, followed by 0-6 intervening digits before a second target (T2) and a mask. (**b**) The items used to construct the streams. Experiment 1 used High Similarity streams: 20 target letters (A-Z, omitting I, O, P, Q, Z), and 1 of 4 character masks, embedded in 8 distractor digits (omitting 0). Experiment 2 used high- and low-similarity streams: the same 20 target letters and character masks embedded in random dot patterns. Pre- and post-testing in Experiment 2 used the same 20 target letters and character masks embedded in Klingon distractors

difference in accuracy after training. The statistical details are given below.

Training effects on T2-mask interval Figure 3a shows how the T2-mask interval was reduced with training for the participants (P1-P5) in Experiment 1. Each participant began with an interval of four frames. Figure 3a shows the mean number of frames in each 10 block grouping of trials (600 trials). Two of the participants (P2, P5) completed a total of 100 blocks of training (6,000 trials), P3 completed 90 blocks (5,400 trials), P4 completed 80 blocks (4,800 trials), and P1 completed 50 blocks (3,000 trials). The average T2-mask interval for these five participants is shown in Fig. 3b, and c shows in greater detail the reduction in the T2-mask interval over the first 30 blocks (1,800 trials) for all five participants. All five participants reached asymptotic performance at a T2-mask interval of near zero milliseconds within 20-30 blocks of training.

Repeated measures ANVOA on the T2-mask interval indicated a main effect of block for each of the participants individually (all p values < 0.001 in Fig. 3a) and for the group as a whole in Fig. 3b, $F(9,36) = 18.64$, $p < 0.001$, MSE = 0.201, $p\eta^2 = 0.82$, and Fig. 3c, $F(29,115) = 9.64$, $p < 0.001$, MSE = 0.648, $p\eta^2 = 0.71$. Beyond 30 blocks, there were no longer significant differences in the T2-mask interval, $F(69,191) = 1.07$, $p < 0.36$, MSE = 0.100, $p\eta^2 = 0.28$.

Training effects on target identification accuracy Figure 4a and b show how target accuracy changed between the first and last 10 blocks of trials for the five participants as a group. Figure 4a shows there was little change in T1 accuracy with training (with performance predictably near ceiling at the outset). Repeated measures ANOVA on T1 accuracy indicated a main effect of lag, $F(3,12) = 5.28$, $p < 0.02$, MSE = 0.001, $p\eta^2 = 0.58$, reflecting the small decrease in T1 accuracy for lag 1 compared with the rest, $F(1,12) = 15.37$, $p < 0.01$, MSE = 0.013, $p\eta^2 = 0.57$, but no effect of training, $F(1,12) = 3.09$, $p < 0.16$, MSE = 0.002, $p\eta^2 = 0.41$, and no training x lag interaction, $F(3,12) = 0.63$, $p < 0.62$, MSE = 2.28E-4, $p\eta^2 =$

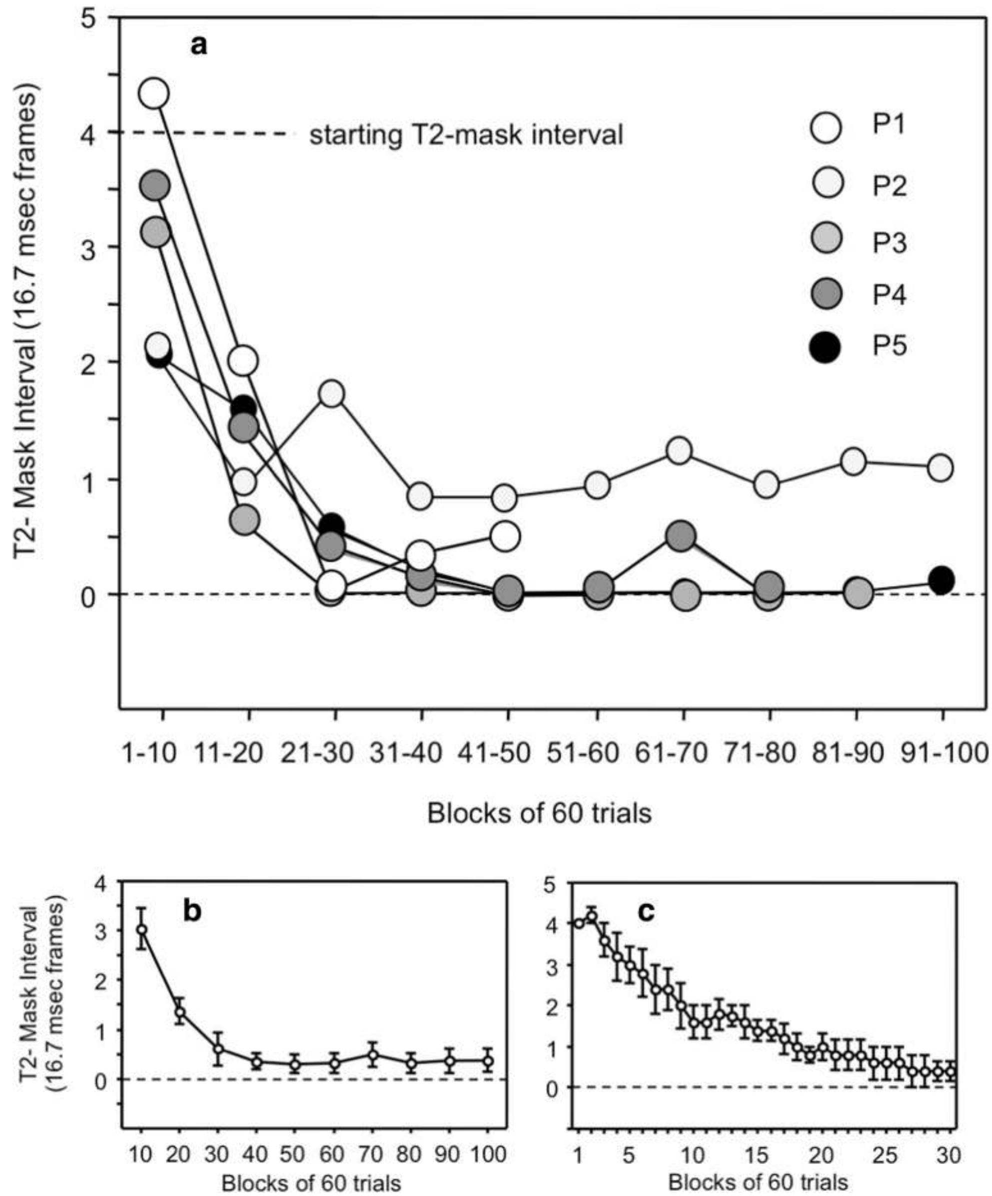

Figure 3 Participants began with a T2-mask interval of 4 frames in Experiment 1. (**a**) Mean T2-mask interval in each successive 10 blocks (600 trials) for each of the 5 participants (P1-P5). (**b**) Mean T2-mask interval for the 5 participants as a group. (**c**) Mean T2-mask interval shown in greater detail over the first 30 blocks (1,800 trials)

0.20, This was all as expected, because the attentional blink is premised on the first target being identified successfully.

Figure 4b shows that T2 accuracy (contingent on T1 being identified correctly), however, showed a significant interaction of lag x phase (first vs. last 10 blocks). Repeated measures ANOVA on T2 accuracy (given T1 correct) indicated a main effect of lag, $F(3,12) = 33.26$, $p < 0.001$, $MSE = 0.006$, $p\eta^2 = 0.89$, that was significant in both the first and the last 10 blocks for the participants as a group. Simple effects tests in the first 10 blocks of trials showed a significant effect of lag, $F(3,12) = 56.43$, $p < 0.001$, $MSE = 0.004$, $p\eta^2 = 0.93$, as did the last 10 blocks of trials, $F(3,12) = 5.38$, $p < 0.02$, $MSE = 0.005$, $p\eta^2 = 0.57$. A significant interaction of training x lag, $F(3,12) = 15.14$, $p < 0.001$, $MSE = 0.003$, $p\eta^2 = 0.79$, indicated that the lag effect was somewhat reduced following training. However, note that the improvement with training in T2 accuracy at lag 1, $F(1,12) = 37.72$, $p < 0.001$, $MSE = 0.114$, $p\eta^2 = 0.76$, was offset by a reduction in T2 accuracy at lags 5 and 7, $F(1,12) = 8.66$, $p < 0.01$, $MSE = 0.026$, $p\eta^2 = 0.42$.

The AB was indexed in each of two ways that are common in the literature. The first was by the difference between T1 and T2 accuracy at lag 1 (T1-T2), which is of course vulnerable to the ceiling effect imposed on T1. The second way was by the difference between T2 accuracy at lag 7 and lag 1 (Lag7-Lag1), which is not vulnerable to ceiling effects when an adaptive procedure contingent on average T2 accuracy is in

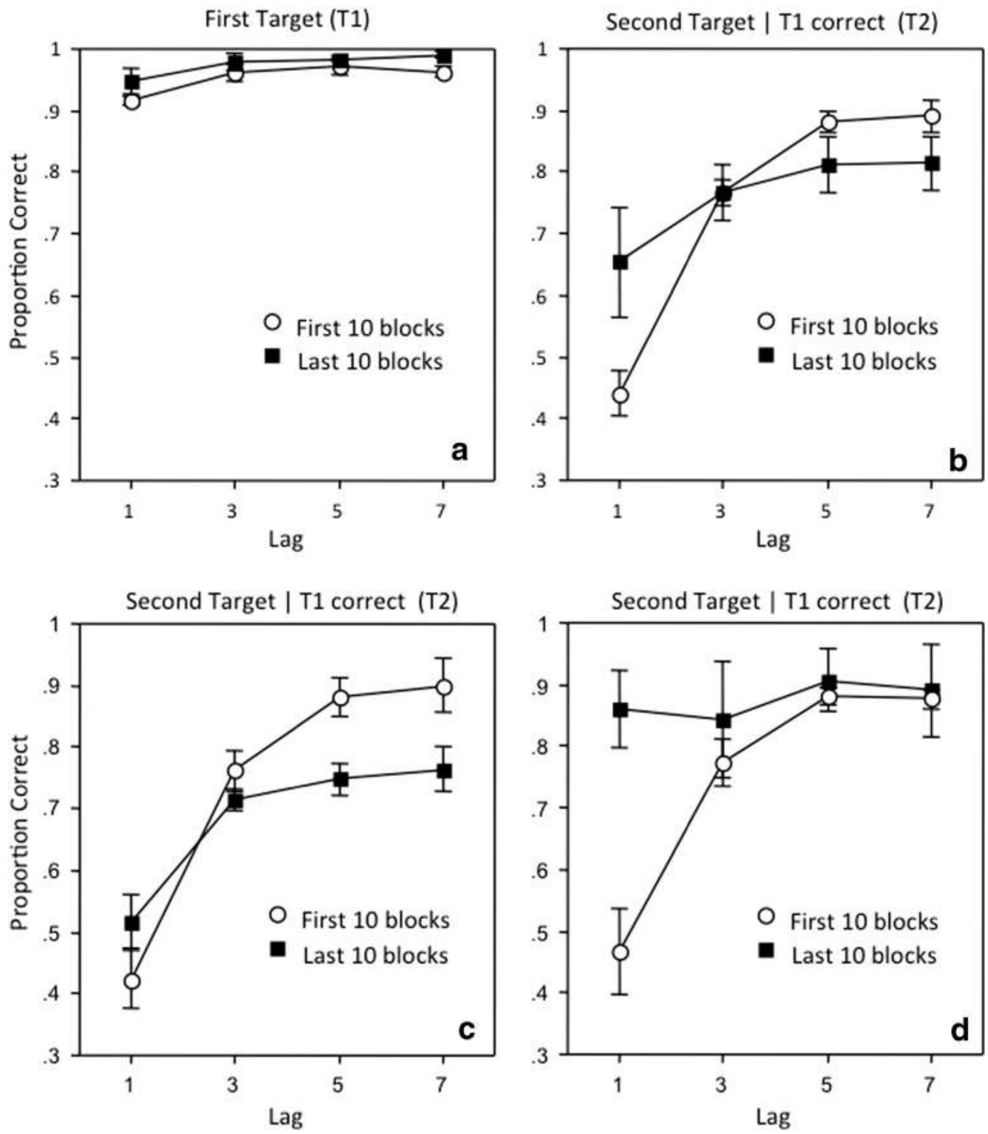

Figure 4 Mean first and second target accuracy in Experiment 1 for the first 10 blocks (600 trials) and the last 10 blocks of testing. (**a**) First target accuracy. (**b**) Second target accuracy. (**c**) Second target accuracy for the 3 participants who still showed an attentional blink in the last 10 blocks. (**d**) Second target accuracy for the 2 participants who showed no attentional blink in the last 10 blocks

effect. Both measures indicated that although the AB had been diminished, it had not vanished with training: mean last blocks T1-T2 = 0.294, $t(4) = 5.77$, $p < 0.01$, mean last blocks Lag7-Lag1 = 0.161, $t(4) = 3.27$, $p < 0.03$.

Figure 4c shows the mean T2 accuracy of three participants who showed a significant lag effect in the last 10 blocks (P2, P3, P5), and Fig. 4d shows the mean T2 accuracy of two participants who did not (P1, P4). Note that although all participants reached an asymptotic T2-mask interval of near zero within 20-30 blocks of training, only two of them were able to overcome any evidence of the attentional blink by conventional measures (i.e., T2 accuracy equal to T1 accuracy levels at short lags). This could either be because these two participants had become genuine "non-blinkers" with sufficient training (Martens et al., 2006) or because reducing the T2-mask interval to zero still left target accuracy at a ceiling level of performance. This question will be pursued in Experiment 2, where we make several changes to the adaptive procedure to bring second target accuracy off the ceiling. These observations were supported by the following statistical analyses.

A repeated measures ANOVA on T2 accuracy scores depicted in Fig. 4c indicated a main effect of lag, $F(3,6) = 18.46$, $p < 0.001$, MSE = 0.002, $p\eta^2 = 0.90$, and a training x lag interaction, $F(3,6) = 4.94$, $p < 0.05$, MSE = 0.017, $p\eta^2 = 0.71$. Simple effects test showed the effect of lag was significant in both the first and last blocks of training, $F(3,6) = 23.73$, $p < 0.001$, MSE = 0.006, $p\eta^2 = 0.92$, and $F(3,6) = 10.60$, $p < 0.001$, MSE = 0.004, $p\eta^2 = 0.84$, respectively. As in the group as a whole, the small nonsignificant improvement with training in T2 accuracy at lag 1, $F(1,6) = 3.75$, $p < 0.10$, MSE = 0.013, $p\eta^2 = 0.38$, was offset by a reduction in T2 accuracy at lags 5 and 7, $F(1,6) = 8.67$, $p < 0.01$, MSE = 0.026, $p\eta^2 = 0.55$. Both measures of the AB indicated that it had not vanished with training in this subgroup: mean last blocks T1-T2 = 0.406, $t(2) = 6.66$, $p < 0.02$, mean last blocks Lag7-Lag1 = 0.247, $t(4) = 3.74$, $p < 0.06$.

A repeated-measures ANOVA on T2 accuracy scores depicted in Fig. 4d also showed a main effect of lag, $F(3,3) = 22.40$, $p < 0.02$, MSE = 0.007, $p\eta^2 = 0.90$, and a training x lag interaction, $F(3,3) = 28.85$, $p < 0.01$, MSE = 0.001, $p\eta^2 = 0.97$, but here the lag effect was significant in the first blocks of training, $F(3,3) = 31.14$, $p < 0.01$, MSE = 0.002, $p\eta^2 = 0.97$, but not in the last blocks, $F(3,3) = 2.33$, $p < 0.26$, MSE = 0.001, $p\eta^2 = 0.71$. For these two participants, the improvement in T2 accuracy did not come at the expense of reduced accuracy in lags 5 and 7. Both measures indicated that the AB had vanished with training in this subgroup: mean last blocks T1-T2 = 0.126, $t(1) = 1.66$, $p > 0.34$, mean last blocks Lag7-Lag1 = 0.031, $t(1) = 2.58$, $p > 0.24$.

Discussion

A central finding of Experiment 1 was that after only 20-30 blocks of training (1,200-1,800 trials) participants were able to maintain second accuracy in the 60-80% range with a T2-mask interval of either 0 (4 participants) or 16.66 milliseconds (1 participant). This meant that our first attempt to use an adaptive procedure to eliminate ceiling effects was not stringent enough. Participants apparently can quickly learn to process rapid sequential information even with no interval between T2 and the mask.

A second finding was that succeeding in second target identification with a reduced T2-mask interval did not eliminate the second target deficit for all participants. Three of the participants continued to show a robust second target deficit after 70-100 blocks (4,200-6,000 trials) even though they had reached asymptote in the T2-mask interval after only 20-30 blocks of trials (Fig. 4c). On the other hand, the two participants who no longer showed a second target deficit after training had already reached that level of accuracy after only 20-30 blocks. Given this variation in performance after identical levels of training, it suggests that individual differences in the magnitude of the AB are a more likely account of training success than any account based on learning (Martens et al., 2006).

A third key finding of Experiment 1 was that reducing the T2-mask interval with training to maintain T2 accuracy below ceiling resulted in a pattern of second target accuracy that traded increased accuracy at short lags with reduced accuracy at long lags (see the crossover interactions in Fig. 4b and c). One way this tradeoff might occur is if training induces stronger temporal orienting toward the earliest items in the stream (short lags), where second target accuracy is lowest at the outset, by definition. If training induces stronger temporal expectations to items early in the stream, then a natural byproduct of this temporal shift in resources would be a reduction in accuracy for second targets appearing later in the stream (long lags; Visser, Ohan, & Enns, 2015; Tang et al., 2014). This account also implies that training did not reduce the structural limit on sequential target processing but may have shifted participant's temporal expectations during the training phase (Tang et al., 2014). It is interesting that training seemed to have the largest effects at lag 1 (Fig. 4c and d), where the two targets have the strongest likelihood of being integrated into a single attentional episode (Akyürek et al., 2012; Akyürek & Hommel, 2005). This opens up the possibility that training, in part, specifically impacted this integration process.

In summary, although it appears that there is some benefit of training on the magnitude of the AB, it is not clear how much of that benefit is an artefact of a change in strategy for some participants, where they trade improvements on lag 1 accuracy for reductions on lags 5 and 7 accuracy (Fig. 4c). For other participants, the reduction in AB with training still cannot be disentangled from a ceiling effect (Fig. 4d).

Experiment 2

The findings from Experiment 1 guided the design of our next experiment, where we implemented four important changes. First, we allowed for two additional increases in task difficulty after the T2-mask interval had been reduced to zero. These included reductions in the duration of stream items ("on time") from 2 frames to 1 frame, and then reductions in the interval between stream items ("off time") from 4 to 0 frames in 1 frame increments.

Second, because Experiment 1 suggested that most of the training effects occurred in the first 30 blocks (1,800 trials), we focused our data collection on that period in Experiment 2 but broadened our sample to include 48 participants in total to increase the diversity of the participant sample and therefore the generality of the findings.

Third, we trained half of the participants with the same stream conditions used in Experiment 1, in which targets and distractors were physically similar (letters amongst digits, Fig. 2b, high similarity), and the other half with more disparate targets and distractors (letters amongst random-dot patches, Fig. 2b, low similarity). We reasoned that if the AB reflects a temporary loss of cognitive control in maintaining a search template for the target (Di Lollo et al., 2005; Taatgen et al., 2009), then specific training on high similarity targets might result in participants' acquiring an attentional set with greater control and precision than training on low similarity targets. Alternatively, it is possible that search under high similarity conditions simply requires more cognitive control, because the task is more difficult, and so equating the overall task difficulty between high- and low-similarity conditions also might equate the training benefits acquired under these conditions.

Fourth, we tested all participants in a version of the AB task that was not used in training (Fig. 2b, Klingon) both before training (pre-test) and after training (post-test). This was important to be able to compare training effects in the two similarity training groups on the same task, because their training experiences were not identical. It also allowed us to test whether the training x lag crossover interaction for second target accuracy observed in Experiment 1 (Fig. 3b and c) was specific to increasing the rate at which stream items were presented (e.g., reduced T2-mask interval) or whether it extended to AB tasks following training more generally.

Method

Participants Forty-eight adult volunteers (26 males, 18–28 years, median = 20 years) with normal or corrected-to- normal visual acuity participated in the study. All were psychology students who received remuneration of $1 for every block of trials completed (60 trials) and provided informed consent before testing. The procedure was approved by the Behavioral Research Ethics Board at the University of British Columbia and was in accordance with guidelines of the American Psychological Association and the Declaration of Helsinki. One half of the participants were assigned to the High Similarity condition (identical to Experiment 1), and the other half were assigned to the Low Similarity condition (Fig. 2b, center panel).

Apparatus, stimuli, and procedure

In addition to the Don't Blink app used in Experiment 1 (High Similarity condition), two other apps were developed for Experiment 2. One was a Low Similarity condition (called Snow Blind; Fig. 2b, center panel) that was identical in all respects to the High Similarity condition except that the digit distractor items were replaced with random dots equal to the average number of dots needed to make the digits 2-9. A third app (called Klingon Task; Fig. 2b, left panel) was installed on an iPad and was used as a testing device in the lab on the initial and final visits of the participants.

Aside from the assignment of participants to one of the two similarity conditions, the methods were very similar to Experiment 1. Participants were told to complete between 20 and 30 blocks of trials within a 4-day period, and they were remunerated at the same rate of $1 per block. However, before leaving with one of the apps installed on their phones, they each completed 5 blocks of testing on the Klingon task. While they were doing this, the experimenter installed the training app onto their phones. When participants returned after 5 days to download their data and get remunerated, they were again tested on the same Klingon task for 5 blocks.

The adaptive procedure also was modified from Experiment 1 to reduce the likelihood of participants reaching a ceiling level of accuracy, as some did in Experiment 1. Once a participant reached ceiling levels of accuracy after reaching the minimal frame rate on the T2-mask interval parameter, if mean T2 accuracy was still greater than 80%, then the on-time for all items in stream was reduced from 2 to 1 (increasing the stream rate from 10 Hz to 12 Hz). Finally, if mean accuracy of T2 was still greater than 80%, then the off-time for all items in the stream was reduced from 4 frames to a minimum of 1 frame (increasing the stream rate from 12 Hz to 15 Hz, etc.).

Participants completed between 1,500-1,800 trials (in 60 trial blocks) of training over a 4-day period, with the adaptive procedure adjusting the T2-mask interval following each block if second target accuracy was greater than 80% or less than 60%.

Results

The results showed that training over 20 blocks (1,200 trials) was very effective, allowing participants to maintain a T2 accuracy rate of 60% to 80%, while at the same time reducing the stream rate parameters by an average of 2 frames (33 milliseconds) for the 24 participants in the high similarity condition and 3 frames (50 milliseconds) for the 24 participants in the low similarity condition. Yet, despite this substantial evidence for improvement in rapid stream perception at a general level, the specific attentional blink effect was not eliminated in either group of participants. After training, T2 accuracy was significantly below T1 accuracy, especially at short lags. Furthermore, the magnitude of the change in T1–T2 accuracy with training was not significantly different for participants trained with either high- or low-similarity distractor streams. When pre- and post-training performance on the Klingon task was compared across these groups, the same two conclusions were drawn: (1) the attentional blink was not eliminated with this amount of training, and (2) there were no differences between the benefits of training on high- versus low-similarity distractors. Analyses of individual differences in the training effects revealed substantial correlations between the magnitude of the attentional blink before and after training. Furthermore, those participants who benefited most from the training—able to identify targets under the most rapid of stream conditions—were those participants who had the smallest AB magnitude before the training regime. The statistical details supporting these conclusions are given below.

Training effects on stream parameters Figure 5 shows how the combined stream variables that were manipulated in the adaptive procedure changed over the first 20 blocks of training. We combined the three variables (T2-mask interval, On

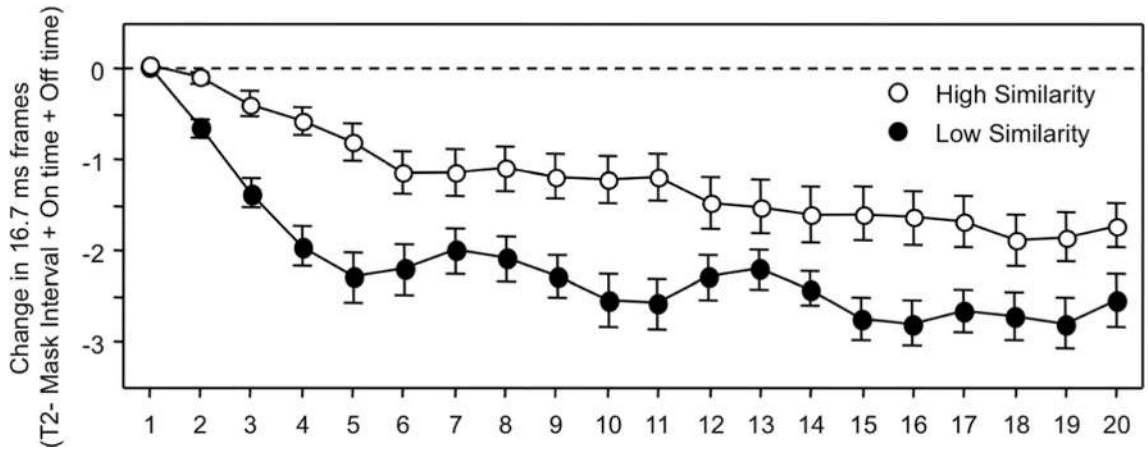

Figure 5 Mean combined values of the three task parameters varied in the adaptive procedure over 20 blocks of training (1,200 trials) in Experiment 2. The task parameters are combined in this graph, because almost all of the change was accounted for by the T2-mask interval in both similarity conditions, with only several participants in each condition showing reductions in On time (high similarity = 6 of 24; low similarity = 9 of 24), and even fewer showing additional reductions in Off time (high similarity = 0 of 24; low similarity = 8 of 24)

time, Off time) in this figure, because the T2-mask interval accounted for almost all of the change in both the High- and Low-Similarity conditions. Only a minority of participants in each condition showed additional reductions in On time (High Similarity = 6 of 24; Low Similarity = 9 of 24) and even fewer showed additional reductions in Off time (High Similarity = 0 of 24; Low Similarity = 8 of 24).

It is clear from Fig. 5 that to keep T2 accuracy in a similar range, participants undergoing Low-Similarity Training were able to tolerate larger changes in the stream parameters than participants undergoing High-Similarity Training. These observations were supported by the following statistical analyses. A main effect of block, F(19,874) = 29.67, $p < 0.001$, MSE = 0.634, $p\eta^2 = 0.39$, indicated a reduction in frame rate with block. A main effect of similarity, F(1,46) = 13.53, $p < 0.001$, MSE = 15.736, $p\eta^2 = 0.23$, reflected that the there was a greater reduction in frame rate for the low- than for the high-similarity condition. A similarity x block interaction, F(19,874) = 2.01, $p < 0.01$, MSE = 0.634, $p\eta^2 = 0.04$, indicated that the rate of decrease was faster for the low than for the high-similarity participants.

Training effects on target identification accuracy Figure 6 shows how target accuracy changed between the first and last 5 blocks of trials for participants undergoing High Similarity (Fig. 6a and b) and Low Similarity (Fig. 6c and d) training. As anticipated, there was little change in T1 accuracy with training, but T2 accuracy showed a significant interaction of lag x phase (first vs. last 5 blocks). Notably, however, the lag effects were still significant in the last 5 blocks for participants in both groups. There also was no hint that training effects were different between the High- and Low-Similarity conditions. These observations were supported by the following statistical analyses.

High Similarity. A repeated measures ANOVA on high similarity T1 accuracy (Fig. 6a) indicated a main effect of lag, F(3,69) = 17.36, $p < 0.001$, MSE = 0.003, $p\eta^2 = 0.43$, reflecting the decrease in T1 accuracy for lag 1 compared with the longer lags, F(1,69) = 49.88, $p < 0.001$, MSE = 0.003, $p\eta^2 = 0.42$, but no effect of training, F(1,23) = 0.25, $p < 0.63$, MSE = 0.087, $p\eta^2 = 0.01$, and no training x lag interaction, F(3,69) = 1.04, $p < 0.38$, MSE = 0.004, $p\eta^2 = 0.04$. T2 accuracy (Fig. 6b) showed a main effect of lag, F(3,69) = 126.14, $p < 0.001$, MSE = 0.013, $p\eta^2 = 0.85$, and a significant interaction of training x lag, F(3,69) = 6.26, $p < 0.001$, MSE = 0.007, $p\eta^2 = 0.21$. As in Experiment 1, the improvement with training in T2 accuracy at lags 1 and lag 3, F(1,69) = 14.84, $p < 0.001$, MSE = 0.007, $p\eta^2 = 0.18$, was offset by a reduction in T2 accuracy at lags 5 and 7, F(1,69) = 4.75, $p < 0.04$, MSE = 0.007, $p\eta^2 = 0.07$.

Low Similarity. Repeated measures ANOVA on low similarity T1 accuracy (Fig. 6c) indicated a main effect of lag, F(3,69) = 3.46, $p < 0.02$, MSE = 0.002, $p\eta^2 = 0.13$, reflecting the decrease in T1 accuracy for lag 1 compared with the longer lags, F(1,69) = 9.71, $p < 0.01$, MSE = 0.002, $p\eta^2 = 0.13$, but no effect of training, F(1,23) = 0.07, $p < 0.81$, MSE = 0.004, $p\eta^2 = 0.00$, and no training x lag interaction, F(3,69) = 0.20, $p < 0.90$, MSE = 0.001, $p\eta^2 = 0.00$. T2 accuracy (Fig. 6d) showed a main effect of lag, F(3,69) = 48.68, $p < 0.001$, MSE = 0.015, $p\eta^2 = 0.68$, and a significant interaction of training x lag, F(3,69) = 13.69, $p < 0.001$, MSE = 0.004, $p\eta^2 = 0.37$. The small improvement with training in T2 accuracy at lag 1,

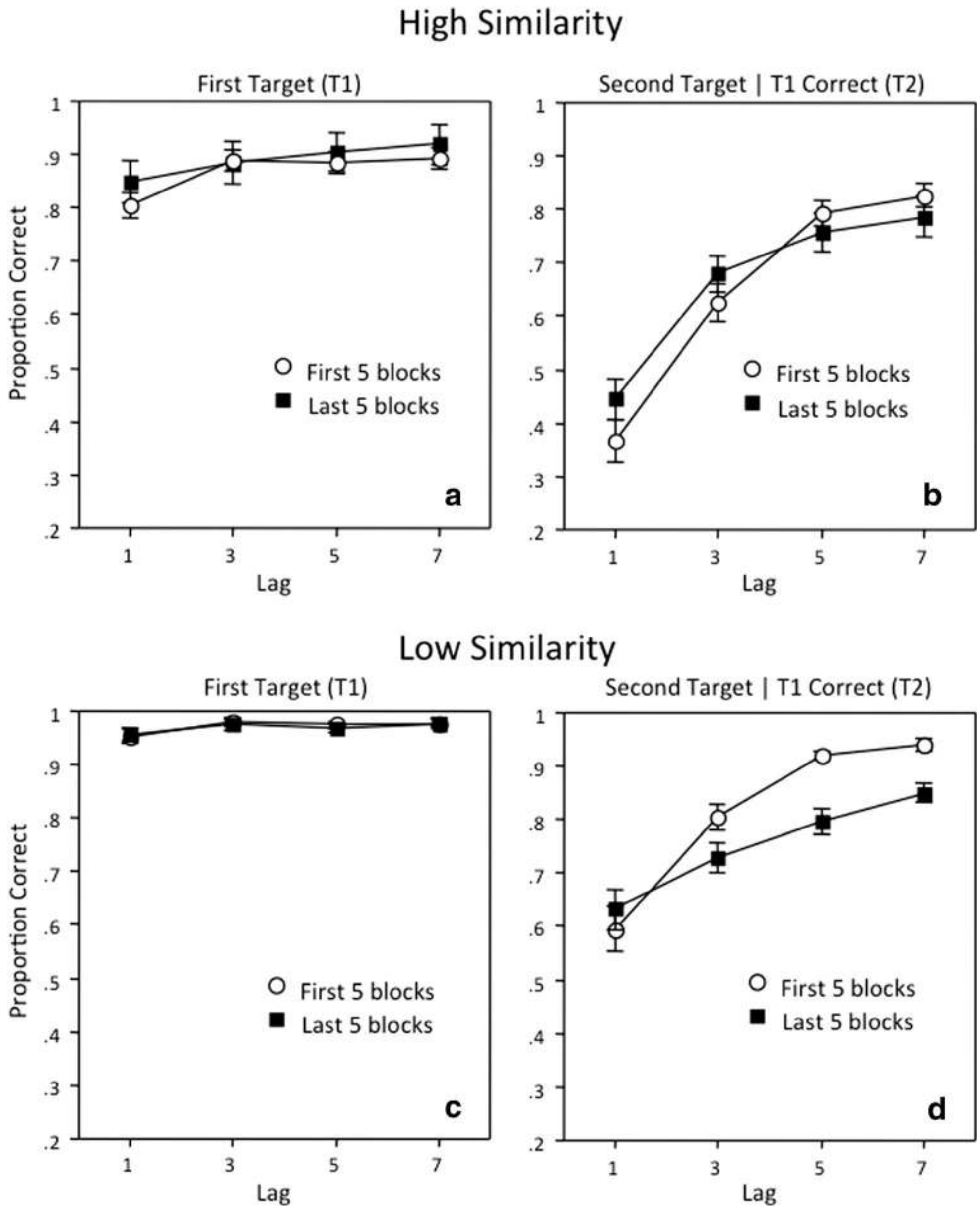

Figure 6 Mean first and second target accuracy in Experiment 2 for the first 5 blocks (300 trials) and the last 5 blocks of testing. (**a, b**) First and second target accuracy in the high similarity condition. (**c, d**) First and second target accuracy in the low similarity condition

F(1,69) = 3.69, $p < 0.06$, MSE = 0.004, $p\eta^2 = 0.05$, was offset by a reduction in T2 accuracy at lags 3, 5, and 7, F(1,69) = 79.84, $p < 0.001$, MSE = 0.004, $p\eta^2 = 0.54$.

A comparison of T2 accuracy in the two similarity conditions indicated that beyond a main effect of similarity, F(1,46) = 22.84, $p < 0.001$, MSE = 0.063, $p\eta^2 = 0.33$, and a similarity x lag interaction, F(3,148) = 5.76, $p < 0.001$, MSE = 0.081, $p\eta^2 = 0.11$, which reflected the smaller attentional blink effect in the low similarity condition, there were no other differences between similarity conditions. In particular, the interaction of similarity x lag x training was not significant, F(3, 138) = 1.73, $p < 0.17$, MSE = 0.006, $p\eta^2 = 0.04$.

As in Experiment 1, we indexed the AB by both the difference between T1 and T2 accuracy at lag 1 (T1-T2) and by the difference between T2 accuracy at lag 7 and lag 1 (Lag7-Lag1). For each of these measures, we conducted an ANOVA examining the factors of training (first blocks, last blocks) and similarity (high, low), as well as *t*-tests comparing the mean AB in the post-test to zero. For the T1-T2 measure there were no significant effects (all $p > 0.10$). For the Lag7-Lag1 measure, there was a significant effect of similarity, with a smaller AB in the low- than in the high-similarity condition, F(1,46) = 6.11, $p < 0.02$, $p\eta^2 = 0.12$., and a significant effect of training, with a smaller AB in the last than in the first blocks, F(1,46) = 26.76, $p < 0.001$, $p\eta^2 = 0.37$. There were no significant interactions, $p > 0.94$. However, for both measures, the AB in the last blocks also was significantly greater than zero: mean high similarity T1-T2 = 0.401, t(23) = 9.78, $p < 0.001$; mean low similarity T1-T2 = 0.323, t(23) = 8.73, $p < 0.001$; mean high similarity Lag7-Lag1 = 0.340, t(23) = 8.10, $p < 0.001$; and mean low similarity Lag7-Lag1 = 0.218, t(23) = 5.60, $p < 0.001$.

Training effects on pre- and post-testing on a related task Figure 7 shows how target accuracy changed between pre- and post-testing on the Klingon task for participants undergoing High Similarity (Fig. 7a and b) and Low Similarity (Fig. 7c and d) training. On this task, there were significant improvements with training for both T1 and T2. There also were significant interactions between lag and testing phase, with the T2 lag effects being significant in the last 5 blocks for the participants in both groups. As with the training AB task, there was no hint that training in the high- versus low-similarity conditions influenced transfer to the Klingon task in a differential way. These observations were supported by the following statistical analyses.

A mixed-effects ANOVA on T1 accuracy pointed only to a slight difference in the lag effect during pre-testing for the high- and low-similarity groups. Specifically, there was a lag

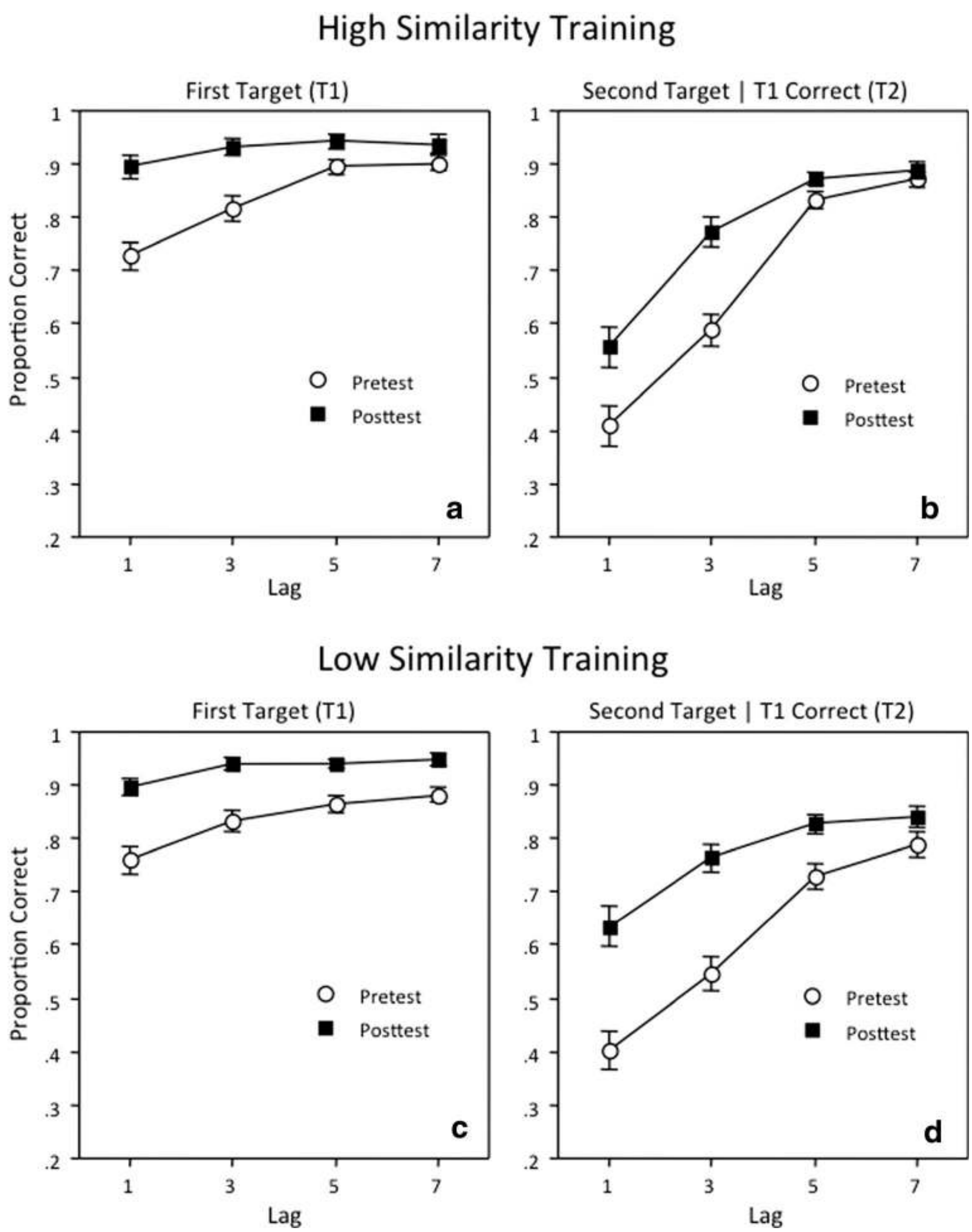

Figure 7 Mean pre- and post-training target accuracy in Experiment 2 on the Klingon distractor task. (**a, b**) First and second target accuracy in the high similarity condition. (**c, d**) First and second target accuracy in the low similarity condition

x similarity group interaction during the pre-test phase ($p < 0.05$) but not during the post-test phase. This was a reflected in a significant three way interaction, $F(3,138) = 2.97$, $p < 0.03$, MSE = 0.002, $p\eta^2 = 0.06$. The same analysis on T2 accuracy indicated only one significant effect involving similarity. This was a significant similarity x lag interaction, $F(3,138) = 4.17$, $p < 0.01$, MSE = 0.014, $p\eta^2 = 0.08$, which indicated that the lag effect was a smaller in the low-similarity training group than in the high-similarity group, similar to results from previous studies that have examined the influence of target-distractor similarity on the AB (Visser, Bischof, & Di Lollo, 2004). This finding runs counter to the prediction that more difficult training will reduce the attentional blink in comparison to easier training. All other effects involving similarity were not significant. This meant that the improvement in the attentional blink with training did not differ between similarity training groups, similarity x training x lag: $F(3,138) = 0.87$, $p < 0.46$, MSE = 0.004, $p\eta^2 = 0.01$, and neither did the overall improvement differ between pre- and post-testing after averaging over lag, because the similarity x training interaction was not significant: $F(1,46) = 2.49$, $p < 0.13$, MSE = 0.027, $p\eta^2 = 0.05$.

We indexed the AB in the Klingon task by both AB measures and conducted *t*-tests comparing the measures to zero. For the T1-T2 measure, there was only a significant training x similarity interaction, $F(1,46) = 8.53$, $p < 0.01$, MSE = 0.009, $p\eta^2 = 0.16$, reflecting a reduction in the AB with training in the low similarity condition ($p < 0.05$) but not in the high similarity condition ($p > 0.50$). The Lag7-Lag1 measure yielded a significant effect of similarity, with the AB significantly smaller in the low- than in the high-similarity condition, $F(1,46) = 4.66$, $p < 0.04$, $p\eta^2 = 0.09$, and a significant effect of training, with a larger AB in the last than in the first blocks, $F(1,46) = 68.94$, $p < 0.001$, $p\eta^2 = 0.60$. There were no significant interactions, $p > 0.18$. For both measures the AB in the post-test was significantly greater than zero: mean high similarity T1-T2 = 0.339, $t(23) = 10.27$, $p < 0.001$, mean low similarity T1-T2 = 0.261, $t(23) = 8.16$, $p < 0.001$, mean high similarity Lag7-Lag1 = 0.332, $t(23) = 8.97$, $p < 0.001$, and mean low similarity Lag7-Lag1 = 0.205, $t(23) = 5.69$, $p < 0.001$.

Individual differences in training effects Figure 8 shows the relation between the initial size of the attentional blink in Experiment 2 participants (mean T1-T2 difference at Lag 1 in the first 5 blocks) and the degree to which they were able to reduce the stream parameters with training (increase in stream rate over 20 blocks of training). The negative correlation, $r(46) = -0.456$, $p < 0.001$, suggests that those participants with relatively smaller attentional blinks before training also were those that changed their stream parameters the most with training. A similar-sized negative correlation was evident in the Klingon pre-test data, $r(46) = -0.316$, $p < 0.03$. Conducting the correlations with the Lag7-Lag1 measure of the AB led to the same conclusion: AB in the first 5 blocks of training, $r(46) = -0.406$, $p < 0.01$; AB in the Klingon pre-test, $r(46) = -0.440$, $p < 0.001$.

Figure 9a shows the relation between the AB (mean T1-T2 difference at Lag 1) in the first and last 5 blocks for the 48 participants in Experiment 2. The positive correlation, $r(46) = 0.535$, $p < 0.001$, suggests that those participants with relatively larger attentional blinks prior to training tended to be those with relatively larger blinks after training. Figure 8b shows the relation between the AB in the Klingon pre-test and the Klingon post-test for the same 48 participants. The positive correlation, $r(46) = 0.553$, $p < 0.001$, again shows that participants with relatively larger attentional blinks in the Klingon task prior to training tended to be those with relatively larger blinks after training. Conducting the correlations with the Lag7-Lag1 measure of the AB led to the same conclusion: AB in the first 5 blocks of training, $r(46) = 0.652$, $p < 0.001$; AB in the Klingon pre-test, $r(46) = 0.739$, $p < 0.001$.

The partial correlation between the AB (mean T1-T2 difference at Lag 1) in the first and last 5 blocks, after controlling for changes in stream parameters with training, was similar in size to the simple correlation, $pr(45) = 0.434$, $p < 0.002$. A multiple regression analysis to predict the AB in the last 5 blocks of training (criterion variable), that included both the AB in the first 5 blocks and the parameter gain variable as predictor variables, indicated a significant contribution of the initial AB, standardized $B = 0.448$, $t(45) = 3.23$, $p < 0.0023$, but no significant contribution from the parameter gain variable, standardized $B = -0.190$, $t(45) = 1.37$, $p < 0.178$; overall $R = 0.561$, $F(2, 45) = 10.32$, $p < 0.001$. Conducting the analyses with the Lag7-Lag1 measure of the AB led to the same conclusion: $pr(45) = 0.569$, $p < 0.001$; standardized $B = 0.545$, $t(45) = 4.65$, $p < 0.001$, and an independent and significant negative contribution from the parameter gain variable, standardized $B = -.262$, $t(45) = 2.24$, $p < 0.03$; overall $R = 0.694$, $F(2, 45) = 20.96$, $p < 0.001$.

A similar pattern of relationships held for the Klingon distractor pre- and post-test data. The partial correlation between the attentional blink pre- and post-testing after controlling for changes in stream parameters was significant, $pr(45) = 0.487$, $p < 0.001$, and multiple regression indicated that post-test AB magnitude was predicted by the pre-test AB magnitude, standardized $B = 0.463$, $t(45) = 3.74$, $p < 0.001$, with an independent and negative contribution from the parameter gain variable, standardized $B = -0.285$, $t(45) = 2.30$, $p < 0.03$; overall $R = 0.615$, $F(2,45) = 13.71$, $p < 0.001$. Conducting the analyses with the Lag7-Lag1 measure of the AB led to the same conclusion: $pr(45) = 0.664$, $p < 0.001$; standardized B for the pre-test AB = 0.628, $t(45) = 5.96$, $p < 0.001$, standardized B for the parameter gain variable = -0.251, $t(45) = 2.38$, $p < 0.02$; overall $R = 0.772$, $F(2, 45) = 33.26$, $p < 0.001$.

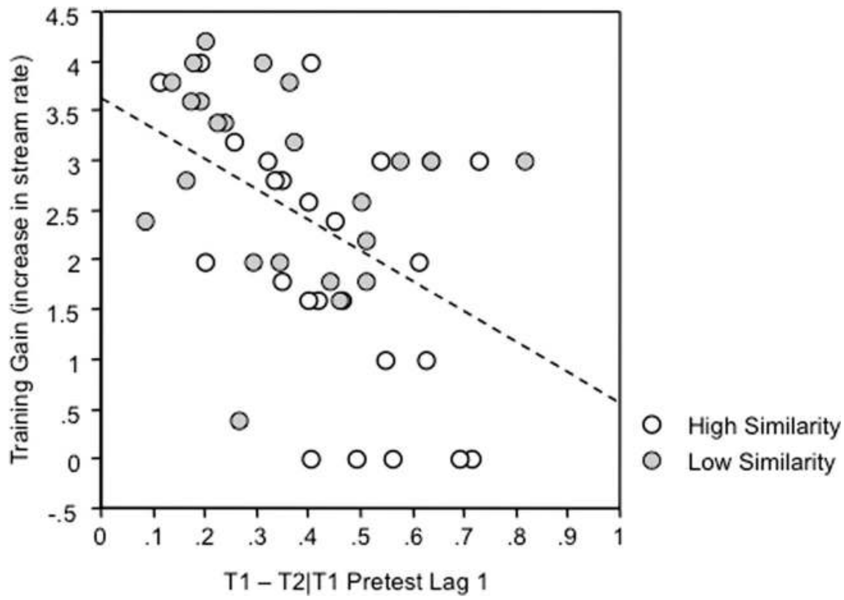

Figure 8 Scatterplot of the relation between the initial size of the attentional blink in Experiment 2 participants (mean difference between T1 and T2 accuracy in Lag 1 in the first 5 blocks) and the degree to which they were able to reduce the stream parameters with training (increase in stream rate over 20 blocks of training)

Discussion

These results are decisive in supporting several conclusions. First, undergoing extensive training in some aspects of rapid stream perception does not guarantee the elimination of the AB, at least not when the AB is defined in the conventional way as the difference in T1–T2 accuracy at short lags. Second, there does not appear to be a measurable difference in the AB when training occurs with high-similarity distractors than when it occurs with low-similarity distractors. We hasten to add that training with low-similarity distractors certainly allows participants to identify targets in streams with faster rate parameters than training with high-similarity distractors. Yet, this difference in success at general processes of rapid stream perception does not appear to translate into any specific differences in the size of the attentional blink. Third, the ineffectiveness of differential training experiences also was seen in the Klingon task, which, unlike the high- and low-similarity training conditions, did not differ at all in its stimulus conditions between pre- and post- testing sessions.

It is worth noting that the crossover interaction of training x lag that occurred for the task participants were trained on in both Experiment 1 (Fig. 3b and c) and Experiment 2 (Fig. 7b and d) did not occur in the Klingon task. Note that in the Klingon task the adaptive procedure was not implemented, and so ceiling effects could not be avoided. Here the improvement for T2 accuracy was largest for the shortest lags and least for the longest lags. This is consistent with the notion that an increase in stream rate (e.g., the reduced T2-mask interval, on time, off time) focuses temporal expectations on targets at the beginning of the stream (Visser et al., 2015; Tang et al., 2014). When these constraints were removed (as they were in the Klingon task, with its constant stream rate in pre- and post-testing) accuracy on longer-lag second targets was no longer differentially affected by training.

Perhaps the most important findings from this experiment arise from the analyses of individual differences. Collectively, these analyses point to considerable stability within individuals across training. Consider first that despite quite large differences in the magnitude of the AB across individuals prior to testing, extensive training in rapid stream perception did little to change the rankings of individuals within the distribution of attentional blink performance. Second, despite some individuals experiencing considerable success in identifying targets under increasingly rapid stream conditions, there was no indication that individuals who accrued greater training gains in rapid stream perception also benefited more in reducing their attentional blink with training. Indeed, there was a substantial and significant correlation in the opposite direction, indicating that those participants who benefited most from rapid stream perception training were the same participants who already had the smallest AB magnitude prior to training. Third, training on high- versus low-similarity distractors had an effect on how rapidly items could be presented while maintaining 60-80% accuracy on T2, but had no positive influence on pre- versus post- rankings on the AB measure. Taken together, these patterns in the individual differences data suggest that extensive training (on either high or low similarity tasks) had little influence on the relative standings of individuals with respect to the AB.

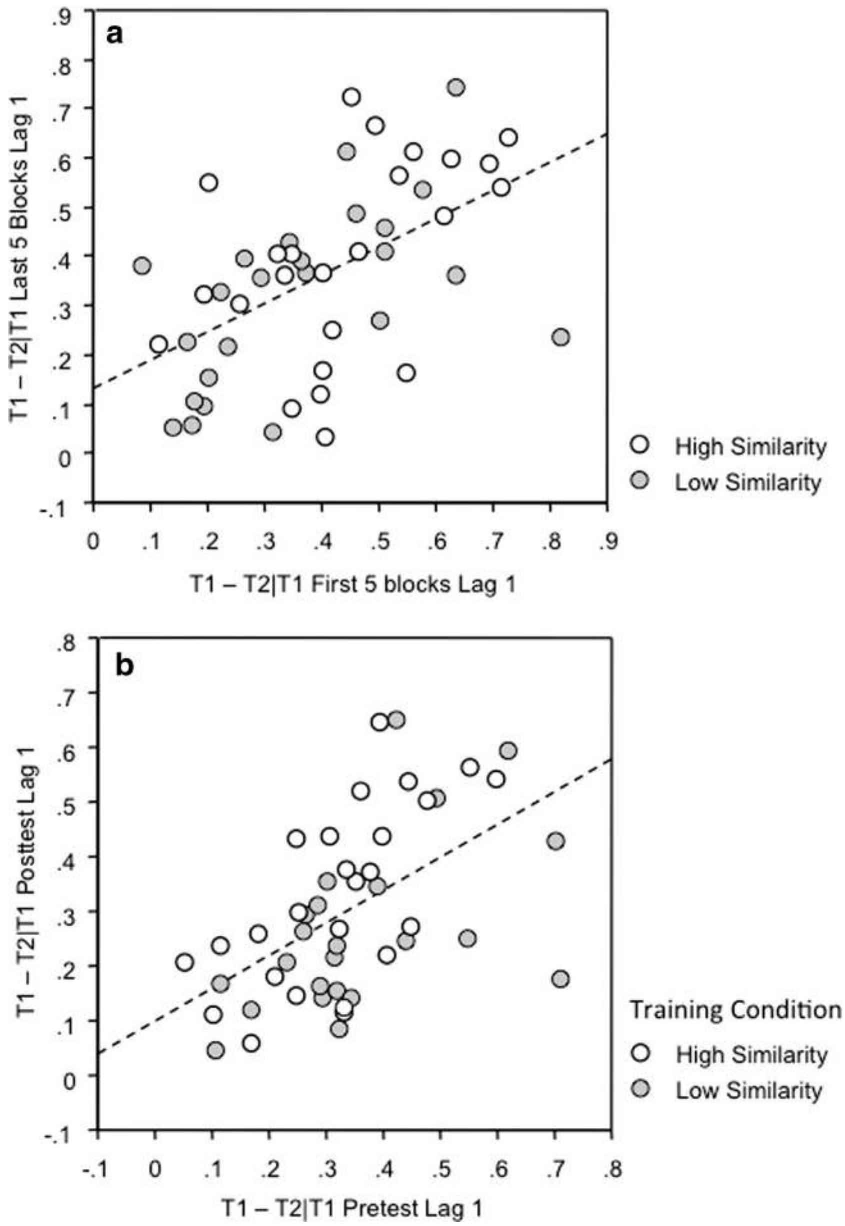

Figure 9 (**a**) Scatterplot in Experiment 2 of the relation between the attentional blink (T1–T2 accuracy in Lag 1) in the first and last 5 blocks of training for the 48 participants. (**b**) Scatterplot of the relation between the attentional blink (T1–T2 accuracy in Lag 1) in the pre- and post-testing phases for the Klingon distractor task. High- and low-similarity training participants are shown in different colors. The significant correlation means that, independent of training, participants tended to maintain their relative rankings with respect to the size of the attentional blink after training

General discussion

The main purpose of this study was to examine two challenges to the widely held view that the attentional blink reflects a structural limit in visual-temporal information processing (Goodbourn et al., 2016; Joseph, Chun, & Nakayama, 1998) rather than the consequence of limited experience in the performance of a specific laboratory task (Awh et al., 2004). The first of these challenges is the apparent elimination of an AB with training (Braun, 1998, Choi et al., 2012; Taatgen et al., 2009). The second is the apparent existence of a small number of individuals for whom the AB task poses no measureable challenges (Martens et al., 2006; Martens & Valchev, 2009). Our rationale began with the observation that interpretation of previous studies in these two literatures was clouded by ceiling effects. This meant that reported failures to detect a measureable T2 deficit might reflect insensitive measurement rather than an absence of the AB.

In the present study, we eliminated ceiling effects by making adaptive adjustments to stream variables, such as the T2-mask interval and presentation rate, to keep second target accuracy within a measureable range, even after extensive training. In Experiment 1, we did this for a small number of participants to establish some baseline parameters for a more extensive study in Experiment 2, involving 48 participants, two different levels of training difficulty, and a common pre- and post-test on which the two groups could be compared.

We reasoned that if the AB is a consequence of structural limits on rapid sequential processing, then it should persist in the face of extensive training, provided that accuracy remains in a measurable range throughout the training period. This outcome would be consistent with there being a hard structural limit on sequential information processing (Joseph et al., 1998). Alternatively, if the limitations reflected in the AB can be ameliorated with practice, then training on the AB task should eliminate the second target deficit, even when second target accuracy remains in a measurable range. This outcome would be consistent with some aspects of the two-target identification task becoming automated or habitual through training.

The results were decisive in showing that the conventional measure of the AB—a lag-dependent difference between T1 and T2 accuracy—persists robustly in the face of extensive training on rapid stream perception. Although there was some reduction in the AB with training, this reduction could not be disentangled from a change in strategy, whereby improvements on lag 1 accuracy were traded for reductions on lags 5 and 7 accuracy (Figs. 4c, 6b, and d). When we examined pre- versus post-training performance on a related task where the adaptive procedure had not been implemented (Fig. 7b and d), we observed only the usual reductions in the AB that occur when ceiling effects are not controlled. Moreover, the difficulty of the training task had no measureable influence on this related task, despite one group (low similarity) becoming much more proficient in rapid stream perception than another group (high similarity).

The most important and surprising results of this study came from our examination of individual differences in AB magnitude and in the benefits of training on rapid stream perception. Our study of 48 participants in Experiment 2 confirmed the observation of previous studies (Martens et al., 2006; Martens & Valchev, 2009), that the AB differs substantially between participants at baseline. It also documented that some participants benefit much more from rapid stream training than others (as indexed by the decrease in their stream parameters). However, the surprise was that it was participants who had the smallest AB in baseline that experienced the greatest gains in rapid stream perception through training. Beyond that unexpected training benefit for "non-blinkers"; however, the relative ranking of participants before and after training remained remarkably stable. Furthermore, when we tried to predict the magnitude of the AB post-training, the best predictor was the initial magnitude of AB prior to training. Any contribution of the training benefit measure to post-training AB magnitude was independent and *in the opposite direction*!

Implications for theory

These findings have quite different implications for the two literatures that prompted our original question. With regard to the training literature, the present results suggest that training actually has two separable effects on T2 accuracy. One effect is on more general perceptual and cognitive processes related to detecting and identifying targets in rapid streams of nontargets. The second effect is specifically on the processes that underlie T2 impairments arising from T1 processing, i.e., the conventional AB. Our training regime, which involved gradually increasing the rate of stream items as training progressed, to maintain T2 accuracy in the 60% to 80% range, appeared to have a significant influence on general processes without having much influence on the AB-specific processes. It could even be argued that our design saturated training on the general processes (as suggested by the asymptotic effects of training on the stream parameters) while leaving the conventional measure of the AB (lag dependent T1–T2 difference) relatively unscathed.

To illustrate, consider the influence of these putatively separate sources of influence (stream general processes and AB-specific processes) on the conventional measurements of the AB: the difference between T1 and T2 accuracy at short lags and the difference between long and short lags for T2 accuracy. As shown in Fig. 6b and d, prior to training, a substantial AB is measured, as indicated by the data in white open discs in these figures. Without adaptive adjustment of the overall level of task difficulty, these curves would move to ceiling as training progresses, as they have in all previous training studies, and as they did on the Klingon task. But with adaptive adjustments to task difficulty, the mean (center of the curve) is guaranteed to remain at approximately the same overall level of accuracy. The question is, will the function of accuracy over lag flatten out as training progresses, consistent with the elimination of the AB, or will the lag-dependent function remain, consistent with an AB, even after there have been large improvements in stream general processes that determine the overall average of the curve? The data shown in the black discs of Fig. 6b and d clearly support the latter interpretation.

As the above example illustrates, the convention of taking the simple difference between T1 and T2 to measure changes in the attentional blink cannot by itself distinguish between general and AB-specific training effects when ceiling effects are in play. This is because improvements in general processes alone are potentially sufficient to push T2 performance to ceiling, thus appearing to eliminate the AB even when lag-dependent specific processes are unaffected. This is especially true, because T1 accuracy in conventional AB studies also is on ceiling, by definition, because the task is relatively easy and the AB is defined as T2 accuracy contingent on T1 being reported correctly. This means that improvements to general processes, which would likely be indexed by changes in T1

Table 1 Mean magnitude of the attentional blink (standard error in parentheses) for two extreme groups of participants: eight participants with the smallest AB and eight with the largest AB in the first 5 blocks of training. Also shown is the mean T1–T2 accuracy on lag 1 for the Klingon task and the mean parameter gain for these two groups. The attentional blink is indexed by both the difference between T1 and T2 at lag 1 (T1-T2) and by the difference in T2 accuracy for Lag 7 and Lag 1 (Lag7-Lag1)

Extreme Group	Training AB		Klingon AB		Parameter Gain
	First 5 blocks	Last 5 Blocks	Pretest	Postest	
T1-T2					
Smallest AB	0.164 (0.019)	0.266 (0.058)	0.267 (0.045)	0.195 (0.051)	3.2 frames
Largest AB	0.677 (0.027)	0.534 (0.057)	0.538 (0.043)	0.508 (0.053)	2.0 frames
Lag7-Lag1					
Smallest AB	0.247 (0.041)	0.209 (0.058)	0.293 (0.052)	0.188 (0.046)	3.2 frames
Largest AB	0.648 (0.041)	0.456 (0.067)	0.635 (0.026)	0.504 (0.054)	2.0 frames

accuracy, cannot be detected, leaving the source of training effects on T2 unknown. With this in mind, our conclusion is that all previous training studies have not adequately distinguished between general and AB-specific training effects on T2 accuracy and therefore might have misattributed an improvement in T2 accuracy to the wrong source. The present design and analysis leads us to the conclusion that AB-specific processes are influenced very little, if at all, by extensive training with the AB task.

Although our results lend little support to the notion that training can eliminate central limitations underlying the AB, we believe they are more supportive of the past evidence that some individuals are "non-blinkers" who are largely immune to the AB (Martens et al., 2006; Martens & Valchev, 2009). This support comes from several independent pieces of evidence, including the substantial correlations between the magnitude of the AB pre- and post-training on two different AB tasks. Perhaps the strongest support, however, is to be found in the negative correlation that we observed (for both the training AB task and the Klingon task) between the initial magnitude of the AB and an individual's ability to benefit from rapid stream training (Fig. 9). This relationship makes it clear that those individuals best prepared to benefit from training are those with an AB that is relatively small to begin with. To the extent that training could potentially influence both general and specific processes, this finding implies that "non-blinkers" were already immune to the T2 deficit and that training did little to enhance this already-existing benefit. The counter-argument, of course, is that non-blinkers would be expected to require more stringent stream parameters than blinkers, to reduce their performance to a measurable level, given the existing differences in performance. However, the fact that a large difference in the stream parameters between blinkers and non-blinkers remained, even after parameters reached asymptote, implies that there is still some difference in ability between blinkers and non-blinkers that persists, suggesting that a real qualitative disparity exists between these groups.

To amplify this point, Table 1 illustrates the stability of AB measurements and their relationship to an individual's ability to benefit from training. We focused on those participants with the smallest and the largest initial AB estimates on the first blocks of testing (4 each in the low- and high-similarity conditions). Note that whether we selected the extreme three, five, or ten individuals in each group had no influence on the conclusions. The magnitude of the AB varies little with training in either the training AB task or the Klingon task. These data clearly illustrate that while training on rapid stream perception was effective to improve general processing (as indexed by the observed gain in stream rate over the course of training shown in the last column), it did little to alter the magnitude of the AB, and it was most effective for participants who already had the smallest AB magnitude before training.

We therefore conclude that removing the ceiling on the AB measurement has led to very different conclusions about the two challenges to the structural limits' interpretation that prompted our experiments. While we think the previous training studies arguing that the AB can be eliminated are flawed in their design, we also concluded that there are participants who experience very little AB to begin with, supporting the claim by Martens et al. (2006) for the existence of "non-blinkers." Our design contributes new evidence to this claim by showing the unique ability of low- or non-blinkers to benefit from stream-general training. The ability of these individuals to benefit most from rapid-stream training is consistent with the interpretation that non-blinkers are likely those individuals with stable cognitive characteristics that include a high level of perceptual speed and large operational spans in their working memory (Arnell, Stokes, MacLean, & Gicante, 2010).

Author Notes This work was supported by Australian Research Council Grant Nos. DP120102313 to T.A.W.V. and J.T.E., as well as by a Natural Sciences and Engineering Research Council of Canada grant No. RGPIN-2013-36796 to J.T.E. The University of Western Australia also provided travel support and accommodation to J.T.E.

References

Akyürek, E. G., Eshuis, S. A., Nieuwenstein, M. R., Saija, J. D., Başkent, D., & Hommel, B. (2012). Temporal target integration underlies performance at lag 1 in the attentional blink. *Journal of Experimental Psychology. Human Perception and Performance, 38,* 1448–1464.

Akyürek, E. G., & Hommel, B. (2005). Target integration and the attentional blink. *Acta Psychologica, 119,* 305–314.

Arnell, K. M., Stokes, K. A., MacLean, M. H., & Gicante, C. (2010). Executive control processes of working memory predict attentional blink magnitude over and above storage capacity. *Psychological Research, 74*(1), 1.

Awh, E., Serences, J., Laurey, P., Dhaliwal, H., van der Jagt, T., & Dassonville, P. (2004). Evidence against a central bottleneck during the attentional blink: Multiple channels for configural and featural processing. *Cognitive Psychology, 48*(1), 95–126.

Bowman, H., & Wyble, B. (2007). The simultaneous type, serial token model of temporal attention and working memory. *Psychological Review, 114*(1), 38–70.

Braun, J. (1998). Vision and attention: The role of training. *Nature, 393*(6684), 424–425.

Brehaut, J. C., Enns, J. T., & Di Lollo, V. (1999). Visual masking plays two roles in the attentional blink. *Attention, Perception, & Psychophysics, 61*(7), 1436–1448.

Choi, H., Chang, L. H., Shibata, K., Sasaki, Y., & Watanabe, T. (2012). Resetting capacity limitations revealed by long-lasting elimination of attentional blink through training. *Proceedings of the National Academy of Sciences, 109*(30), 12242–12247.

Chun, M. M., & Potter, M. C. (1995). A two-stage model for multiple target detection in rapid serial visual presentation. *Journal of Experimental Psychology: Human Perception and Performance, 21*(1), 109–127.

Dell'Acqua, R., Dux, P. E., Wyble, B., & Jolicœur, P. (2012). Sparing from the attentional blink is not spared from structural limitations. *Psychonomic Bulletin & Review, 19*(2), 232–238.

Di Lollo, V., Kawahara, J. I., Ghorashi, S. S., & Enns, J. T. (2005). The attentional blink: Resource depletion or temporary loss of control? *Psychological Research, 69*(3), 191–200.

Giesbrecht, B., & Di Lollo, V. (1998). Beyond the attentional blink: Visual masking by object substitution. *Journal of Experimental Psychology. Human Perception and Performance, 24*(5), 1454–1466.

Goodbourn, P. T., Martini, P., Barnett-Cowan, M., Harris, I. M., Livesey, E. J., & Holcombe, A. O. (2016). Reconsidering temporal selection in the attentional blink. *Psychological Science, 27*(8), 1146–1156.

Jolicœur, P., & Dell'Acqua, R. (1998). The demonstration of short-term consolidation. *Cognitive Psychology, 36*(2), 138–202.

Joseph, J. S., Chun, M. M., & Nakayama, K. (1998). Reply: Vision and attention: The role of training. *Nature, 393*(6684), 425.

Kawahara, J. I., & Enns, J. T. (2009). Selection difficulty and interitem competition are independent factors in rapid visual stream perception. *Journal of Experimental Psychology. Human Perception and Performance, 35*(1), 146–158.

Maki, W. S., & Padmanabhan, G. (1994). Transient suppression of processing during rapid serial visual presentation: Acquired distinctiveness of probes modulates the attentional blink. *Psychonomic Bulletin & Review, 1*(4), 499–504.

Martens, S., Munneke, J., Smid, H., & Johnson, A. (2006). Quick minds don't blink: Electrophysiological correlates of individual differences in attentional selection. *Journal of Cognitive Neuroscience, 18*(9), 1423–1438.

Martens, S., & Valchev, N. (2009). Individual differences in the attentional blink: The important role of irrelevant information. *Experimental Psychology, 56*(1), 18–26.

Olivers, C. N., & Meeter, M. (2008). A boost and bounce theory of temporal attention. *Psychological Review, 115*(4), 836–863.

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of Experimental Psychology: Human Perception and Performance, 18*(3), 849.

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1995). Similarity determines the attentional blink. *Journal of Experimental Psychology: Human Perception and Performance, 21*(3), 653–662.

Taatgen, N. A., Juvina, I., Schipper, M., Borst, J. P., & Martens, S. (2009). Too much control can hurt: A threaded cognition model of the attentional blink. *Cognitive Psychology, 59*(1), 1–29.

Tang, M. F., Badcock, D. R., & Visser, T. A. W. (2014). Training and the attentional blink: Limits overcome or expectations raised? *Psychonomic Bulletin & Review, 21*(2), 406–411.

Visser, T. A. W., Bischof, W. F., & Di Lollo, V. (2004). Rapid serial visual distraction: Task-irrelevant items can produce an attentional blink. *Attention, Perception, & Psychophysics, 66*(8), 1418–1432.

Visser, T. A. W., Ohan, J. L., & Enns, J. T. (2015). Temporal cues derived from statistical patterns can overcome resource limitations in the attentional blink. *Attention, Perception, & Psychophysics, 77*(5), 1585–1595.

Wyble, B., Bowman, H., & Nieuwenstein, M. (2009). The attentional blink provides episodic distinctiveness: Sparing at a cost. *Journal of Experimental Psychology. Human Perception and Performance, 35*(3), 787–807.