Reconsidering Temporal Selection in the Attentional Blink

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Abstract

Two episodes of attentional selection cannot occur very close in time. This is the traditional account of the attentional blink, whereby observers fail to report the second of two temporally proximal targets. Recent analyses have challenged this simple account, suggesting that attentional selection during the attentional blink is not only (a) suppressed, but also (b) temporally advanced then delayed, and (c) temporally diffused. Here, we reanalyzed six data sets using mixture modeling of report errors, and revealed much simpler dynamics. Exposing a problem inherent in previous analyses, we found evidence of a second attentional episode only when the second target (T2) follows the first (T1) by more than 100 to 250 ms. When a second episode occurs, suppression and delay reduce steadily as lag increases and temporal precision is stable. At shorter lags, both targets are reported from a single episode, which explains why T2 can escape the attentional blink when it immediately follows T1 (Lag-1 sparing).

Keywords

attention, visual perception, statistical analysis, open data, open materials

Received 12/22/15; Revision accepted 5/19/16

When two items are presented briefly and in close succession, observers can usually report the first but often fail to report the second. This phenomenon—known as the attentional blink—provides a simple, reliable demonstration of what appears to be a ubiquitous limitation in the processing of visual information. First described by Broadbent and Broadbent (1987), the attentional blink was revealed in a subsequent investigation by Raymond, Shapiro and Arnell (1992) to be attentional, rather than perceptual, in nature. Hundreds of studies have used attentional blink tasks to investigate temporal attention, and rafts of informal and formal models have been generated to account for the findings (see Dux & Marois, 2009, for a review).

On each trial of a typical attentional blink task (see Fig. 1), the observer views a rapidly presented sequence of items and makes judgments about two target items that differ from distractor items in some feature (e.g., red targets among gray distractors), or are distinguished by category (e.g., letter targets among digit distractors), or are accompanied by a cue (e.g., a ring encircling the targets). The observer may be asked to report the identity of each target or simply to indicate its presence or absence.

In an attentional blink study, the number of distractor items appearing between presentation of the first target (T1) and the second target (T2) is varied across trials. Performance for T1 is generally unaffected by its temporal proximity to T2 (this temporal proximity is known as lag and is usually measured by the number of items after which T2 follows T1). However, performance for T2 is severely depressed when it appears within 200 to 500 ms of T1. Curiously, T2 can escape the attentional blink

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when it appears immediately following T1, a phenomenon known as Lag-1 sparing.

In addition to studies of the attentional blink, rapid-serial-visual-presentation tasks more generally can be used to characterize the time course of an episode of attentional selection (Goodbourn & Holcombe, 2015; Martini, 2013; Reeves & Sperling, 1986; Weichselgartner & Sperling, 1987). Across multiple trials, an observer's responses to a cue tend to include not only the target, but also nontarget items in the target's temporal vicinity. Several properties of temporal selection can be estimated from the resulting distribution of responses relative to the target. Here, we considered three of these properties. The efficacy of selection is the probability of reporting an item in the vicinity of the target. The latency of selection is the mean time from the appearance of the target to the appearance of the reported item. Finally, the temporal precision of selection is the dispersion of reported items in the vicinity of the target.

Building on work by Chun (1997), Popple and Levi (2007), and other researchers, Vul, Nieuwenstein, and Kanwisher (2008) analyzed response errors in a fixed temporal window around the targets. They reported that the attentional blink affects not only the efficacy of selection but also its latency and temporal precision. Contrary to standard models of attentional selection in time, their results suggested that when two selection episodes occur in temporal proximity, the dynamics of efficacy, latency, and precision are complex and have distinct time courses.

According to Vul, Nieuwenstein, and Kanwisher (2008), efficacy—proportional to the number of reports in a seven-item window surrounding T2—decreased from Lag 1 to Lag 3 (80–250 ms) and improved gradually from Lag 3 to Lag 10 (250–830 ms). Latency was negative for Lags 1 to 3, such that items before T2 were reported more often than items after T2; for Lag 4 and higher (> 330 ms), selection was delayed, with peak delay at Lag 5 (~415 ms) and a gradual decrease in delay at longer lags. Precision declined rapidly from Lag 1 to a minimum at Lag 3, before rising just as rapidly to return to baseline by Lag 5.

Theories differed as to whether the attentional blink represented a bottleneck (Chun & Potter, 1995) or interference (Shapiro, Raymond, & Arnell, 1994) in working memory, delayed attentional reengagement (Nieuwenstein, Chun, van der Lubbe, & Hooge, 2005; Wyble, Potter, Bowman, & Nieuwenstein, 2011), distractor inhibition (Olivers & Meeter, 2008), or a temporary loss of attentional control settings (Di Lollo, Kawahara, Shahab Ghorashi, & Enns, 2005). The multiple, independent, and complex effects reported by Vul, Nieuwenstein, and Kanwisher (2008) appeared to favor the more complex theories among these. Yet, as Vul and colleagues pointed out, no existing theory could fully account for the findings. The discovery of independent time courses for efficacy, latency, and precision appeared to necessitate a particularly complex model, according to which the attentional blink reflects multiple deficits at different levels of processing.

Fig. 1. Example trial sequences from four attentional blink experiments. Participants view a series of stimuli (distractors and two targets) separated by blank interstimulus intervals. The task is to report the identities of the first target (T1) and second target (T2); in these examples, the item at T2 is the second item to appear following T1 (Lag 2). Stimuli for the Warwick, MIT, and Western samples (a) were white Courier letters, with targets cued by a white ring. Stimuli for the Berkeley sample (b) were Times New Roman letters, with targets discriminated from distractors by color. Stimuli for one condition in the Sydney sample (c) were line drawings of objects, and stimuli for the other condition in the Sydney sample (d) were words naming the same set of objects, with targets either cued by a rectangular frame or discriminated from distractors by color.
However, analyzing errors from a fixed window around the target can result in a distorted picture of the parameters of selection—efficacy, latency, and precision—particularly during Lag-1 sparing and the subsequent attentional blink period. We showed this using a mixture-modeling analysis method, inspired by an earlier application of mixture modeling to color-report errors in studies of working memory (Zhang & Luck, 2008). Mixture modeling improves on the analysis of Vul, Nieuwenstein, and Kanwisher (2008) in two critical ways. First, our model did not use a fixed window of analysis, centered on the time of the target, within which selection-parameter values were calculated; instead, it searched for the set of parameter values that would make the overall distribution of observed errors most likely. Second, it removed the effects of items reported as T2 that were in fact sampled during an initial attentional episode aimed at T1. Applying our mixture model to data from six experiments, we found that temporal selection during the attentional blink does not have the complexity suggested by Vul and colleagues. Our analyses also support the idea that Lag-1 sparing occurs because two items are reported from a single attentional episode.

**Method**

We analyzed data from a convenience sample of six attentional blink experiments, including four of our own. Each met the requirement that a participant’s report indicated which item in the stream was selected by attention, be it a target or a distractor. In these experiments, targets and distractors belonged to the same category; targets were distinguished on the basis of orthogonal features, such as a concurrent cue or a difference in color. Furthermore, the position of the reported items relative to the targets was recorded or could be reconstructed. The temporal distance between the targets and the reported items on each trial formed the basis for our analyses. All data and analysis scripts are available at the Open Science Framework (https://osf.io/fs93m/).

**Procedure**

We used six data sets collected in five studies. The key characteristics of each sample are given below. Further details of participants, apparatus, stimuli, and procedures are given in Table S1 in the Supplemental Material available online.

**University of Warwick data set.** The Warwick data set consisted of previously unpublished data collected by one of the authors (P. Martini) at the University of Warwick. Twenty participants viewed streams of letters presented in white Courier font at a rate of 11.1 items per second, which corresponds to an interstimulus interval (ISI) of 90 ms. Targets were cued by white rings (Fig. 1a).

**Massachusetts Institute of Technology (MIT) data set.** The MIT data set was collected from 12 participants at MIT and first analyzed by Vul, Nieuwenstein, and Kanwisher (2008). The procedure was the same as for the Warwick sample, except that letters were presented at a rate of 12.0 items per second (ISI = 83 ms). We excluded the data from 1 participant because only three of four experimental blocks were recorded for that participant.

**University of Western Ontario data set.** The Western data set was collected from 12 participants by one of the authors (M. Barnett-Cowan) at the University of Western Ontario and published as part of the Reproducibility Project: Psychology (Open Science Collaboration, 2015). This was a direct replication of Vul, Nieuwenstein, and Kanwisher’s (2008) study, so the procedure was the same as for the MIT data set.

**University of California Berkeley data set.** The Berkeley data set was collected and first analyzed by Popple and Levi (2007) at the University of California Berkeley. Twelve observers viewed streams of letters presented in Times New Roman font at a rate of 10.0 items per second (ISI = 100 ms); targets were red items among gray distractors (Fig. 1b), or vice versa. Six of these observers also completed the experiment with letters presented at 15.0, 12.0, 8.5, and 7.5 items per second (ISIs = 67, 83, 117, and 133 ms, respectively).

**University of Sydney data sets.** The two Sydney data sets were collected by two of the authors (I. M. Harris and E. J. Livesey) and previously unpublished, although other experiments in the same series have been published (Livesey & Harris, 2011). Sixty-four observers viewed streams of items at a rate of 9.4 items per second (ISI = 106 ms). In the object condition (n = 32; Fig. 1c), items were line drawings of objects (Snodgrass & Vanderwart, 1980); in the word condition (n = 32; Fig. 1d), items were object names rendered in black, lowercase Arial font. For half of the participants, targets were red (as in Fig. 1c); for the other half, they were surrounded by a rectangular frame (as in Fig. 1d). We excluded 1 participant from the red-target-word condition because of incomplete data.

**Analyses**

**Serial position error (SPE).** On each trial, we calculated the SPE of each target as the difference between the serial position of the reported item and the serial position of the target. For example, correctly reporting the target
item resulted in an SPE of 0, reporting the item following the target resulted in an SPE of 1, and reporting the item preceding the target resulted in an SPE of −1. For combined distributions of T1 and T2 reports at a given lag, we adopted a convention of calculating SPE relative to T2.

**Mixture model.** Our mixture model was a straightforward extension of one we developed for analyzing single-target selection (Goodbourn & Holcombe, 2015), which we adapted recently to analyze dual-target selection in attentional blink tasks (Cellini et al., 2015). The model assumes that a distribution of SPEs, be it of items the participant reported as T1, items reported as T2, or both, comprises up to three categories of trial: (a) T1 trials, in which the reported item was selected during an attentional episode directed at T1; (b) T2 trials, in which the reported item was selected during a second episode directed at T2; and (c) guess trials, in which the response was a random guess.

Target trials (T1 or T2) were drawn from a distribution centered close to the time of the corresponding cue—here, we modeled this with a Gaussian distribution because its parameters can be interpreted intuitively and compared with those derived from Vul, Nieuwenstein, and Kanwisher’s (2008) equations, and because in all cases, the data are well described by a Gaussian model. Guess trials were drawn from a uniform probability distribution across the full range of possible SPE values. The resulting Gaussian-uniform mixture is tapered at the extrema to account for the lower a priori probability of extreme reports; that is, an extreme positive SPE is possible only when targets appear early in the stream, whereas an extreme negative SPE is possible only when targets appear late in the stream. A fuller exposition of the model is provided in the Supplemental Material.

**Model choice.** Particularly at short lags, it is possible that both the T1 and T2 responses reflect a single attentional episode (Wyble et al., 2011). To allow for this possibility, we created two alternative models. The single-episode model (Model 1) contained a single Gaussian distribution, corresponding to a single selection episode; the dual-episode model (Model 2) contained two Gaussian distributions, representing separate episodes for T1 and T2.

We fit both models to the data of each participant at each lag. Reports of T1 and T2 were aggregated into a single distribution, with the SPE of each report coded relative to T2. The best-fitting parameters for each model were found via a likelihood-maximization procedure repeated 100 times with different randomized starting values. We calculated the Bayesian information criterion (BIC) for each model and deemed the preferred model to be the one with the lowest BIC.

**Parameter estimation.** To estimate the properties of attentional episodes, we fit Model 1 and Model 2 to distributions of T1 and T2 reports for each participant and each lag. At each lag, T1-episode parameters were estimated by fitting Model 1 to the distribution of T1 reports. For lags at which Model 1 was preferred, which suggested that all reports were drawn from a single distribution, no T2-episode parameters were estimated. For lags at which Model 2 was preferred, Model 2 was fit to the T2 report distribution to estimate the properties of the T2-directed episode. Note that the transition point between Model 1 and Model 2 preference varied between participants, which introduced some changes in sample size across lags for T2 parameter estimates.

Recall that each fit was a mixture of one or two Gaussian distributions and a pseudouniform guess distribution. The proportion corresponding to the Gaussian distribution nearest the target we referred to as selection’s efficacy. We defined the latency of selection as the mean of the distribution (e.g., zero latency would mean the Gaussian distribution was centered on the target), and the temporal precision of selection as the standard deviation of the distribution. To prevent overfitting of the model to fluctuations in the data produced by guessing, we restricted latency to be no more than four items earlier or later than the target, and precision was restricted to a maximum of four items. For the same reason, we discarded the 5.9% of model fits that converged on these limits.

To summarize the dynamics of efficacy, latency, and precision across data sets, we designated a standard set of lags (100–800 ms, in intervals of 100 ms). These lags were expressed as times, as opposed to numbers of items, because the dynamics of the attentional blink have been shown to reflect time rather than items (Bowman & Wyble, 2007; Vul, Hanus, & Kanwisher, 2008). These lags spanned the range that was common to all samples. When a standard lag did not correspond to a whole number of items, we estimated parameter values by piecewise cubic interpolation.

**Results**

**SPE**

Representative distributions of SPE from the Warwick sample at Lag 1 to Lag 10 are shown in Figure 2. At Lag 1, when T1 and T2 were in consecutive positions in the stream, the combined distribution of T1 and T2 reports was unimodal. This is qualitatively consistent with reports being drawn from a single attentional episode. By Lag 3, the combined distribution was clearly bimodal, which suggests two distinct attentional episodes. However, the T1 and T2 distributions overlapped substantially, and the
Fig. 2. Distribution of serial position errors in a representative data set (Warwick). Serial position error is shown both in terms of the number of items (lower x-axes) and time (upper x-axes). We calculated serial position error by taking the difference between the temporal position in the rapid-serial-visual-presentation stream of the item reported by the participant and the position of the second target (T2). For each of the 10 lags between the first target (T1) and T2, the graphs show the combined distribution of T1 and T2 reports (left) and the distribution of T2 reports only (right). Solid vertical lines show the actual positions of T1 and T2. Dashed curves show the model fit to the data.
distribution of T2 reports alone indicates that these were often drawn from the first episode directed at T1. At longer lags, the proportion of T2 reports that were drawn from the T1 episode declined steadily. By Lag 10, nearly all reports of T2 were drawn from the T2 episode.

**Model choice**

As noted, distributions of SPE at low lags are qualitatively consistent with T1 and T2 being drawn from a single sampling episode. Alternatively, there may in fact be two distinct episodes, but with peaks very close in time. To distinguish these situations, we formally compared two alternative models. Figure 3a shows model preference—the difference in BIC values between the single-episode Model 1 and the dual-episode Model 2—as a function of lag, separately for each sample. At short lags (around 100–250 ms), BIC values were substantially lower for Model 1 than for Model 2, which indicates that the data are best described by a single-episode model. This suggests that T1 and T2 are indeed drawn from one episode. At longer lags, the data are best described by a dual-episode model, which suggests that responses are sampled from two distinct episodes.

One might be concerned that a second episode occurs at short lags but that temporal sampling is too coarse to reveal bimodality in the distribution. In this case, we would expect the transition point, at which the addition of a second episode results in a better model, to emerge earlier at faster presentation rates. Recall that in the Berkeley sample, a subset of participants completed the task at five different rates ranging from 7.5 to 15.0 items per second (ISIs = 67–133 ms). Figure 3b shows model preference as a function of lag, separately for each of the five ISIs. Across a twofold range of presentation rates, the transition point remained consistently between about 100 and 150 ms. In addition, the gradient of the function was steeper at slower presentation rates—that is, preference for Model 2 actually developed more gradually at faster rates. We conclude that the ability of our model to detect the presence of a second distribution was not limited here by the grain of temporal sampling.

**Parameter estimation**

We fit Model 1 and Model 2 to SPE distributions to estimate the efficacy, latency, and temporal precision of selection during the attentional blink. Parameters for T1 were relatively invariant with lag, although there was a numerical trend for higher latency at Lag 1 that may be caused by temporal averaging by the visual system of two cues presented in immediate succession (see Fig. S1 in the Supplemental Material).

Figure 4 shows selection parameters for T2 across participants in all samples (parameter estimates for individual samples are shown in Figure S2 in the Supplemental Material). Conditional accuracy (T2|T1) is the standard metric for attentional blink results; it represents the number of trials on which both targets were reported correctly (SPE of 0) as a proportion of the total number of trials on which T1 was reported correctly. Across all samples, conditional accuracy exhibits the attentional blink profile: sparing at Lag 1, then reduced probability of T2 report for short lags, which resolves to a baseline level at longer lags.

Efficacy is the proportion of trials on which an item from a T2-directed episode is reported; the results indicate that such an episode occurs only if lag exceeds 100 to 250 ms, with the probability of initiating an episode returning monotonically to baseline with increasing lag. For lags below 500 ms, our model found that efficacy is lower than indicated when estimated using the equations of Vul, Nieuwenstein, and Kanwisher (2008). This is because in the equation-based approach, some T2 reports drawn from a T1 attentional episode contribute to T2 efficacy, whereas in the model-based approach they do not. This also accounts for a small dip in efficacy at short lags in the MIT and Western samples. At Lag 1, when T1 and T2 are adjacent, an item sampled from a T1 episode is highly likely to fall within the window of analysis for T2; however, the likelihood decreases as separation between T1 and T2 increases. Thus, efficacy appears to decline until lags at which a separate T2-directed episode is reliably initiated, at which point it begins to rise again toward baseline.

Latency is the center of mass of reports drawn from a T2-directed episode; our model indicates that attentional episodes at short lags are not temporally advanced and return monotonically toward baseline with increasing lag. In contrast, the equation-based analysis of Vul, Nieuwenstein, and Kanwisher (2008) suggests that selection becomes progressively more temporally advanced as lag increases up to about 250 ms, before becoming delayed at later lags. As T1 and T2 move further apart, T2 reports drawn from a T1 episode are increasingly likely to correspond to items that appeared before T2. Accordingly, the mean report error within the equation's window of analysis is shifted toward T1, which results in negative latency. As lag increases, the probability of initiating a T2-directed episode increases. At intermediate lags, the equation's window contains a combination of reports from a T1 episode and reports from a delayed T2 episode; this produces a mean latency around zero. At longer lags, the window contains only reports from the T2 episode, and estimates from the equation and model are in good agreement.
Fig. 3. Model preference as a function of lag, separately for (a) each of the six samples and (b) each of the five interstimulus intervals used for a subset of the Berkeley sample. Model preference is the difference in Bayesian information criterion (BIC) between a model assuming a single attentional episode directed at the first target (Model 1) and an alternative model assuming an additional episode directed at the second target (Model 2). Open shapes on the abscissa show the lag at which the BIC is equal for the two models. Error bars show ±1 SEM.
Fig. 4. Conditional accuracy and second-target (T2) attentional-episode parameters (efficacy, latency, and precision) as a function of lag. Results are collapsed across the six data sets. Conditional accuracy is the number of trials on which both targets were reported correctly as a proportion of the total number of trials on which the first target (T1) was reported correctly. The efficacy of selection is the probability of reporting an item in the vicinity of the target. The latency of selection is the mean time from the appearance of the target to the appearance of the reported item. Finally, the precision of selection is the dispersion of reported items in the vicinity of the target. In all panels, filled shapes indicate that parameter values are significantly different, across participants, from a T1 baseline ($p < .05$, uncorrected for multiple tests); unfilled shapes indicate that the values are not significantly different. For attentional-episode parameters, triangles show values estimated by the equations of Vul, Nieuwenstein, and Kanwisher (2008), and circles show values estimated by mixture modeling. Error bars show parametric 95% confidence intervals, which are larger at shorter lags owing to the smaller proportion of participants for whom there was evidence of a T2 attentional episode. Horizontal bands show the parametric 95% confidence intervals for the corresponding T1 baseline values.

Precision is the temporal dispersion of reports drawn from a T2-directed episode; in contrast to the equation, our model suggests that precision is unaffected by the preceding episode. When precision is calculated using the equation, it appears to worsen before improving across short and intermediate lags. This effect arises because at Lag 1, precision likely reflects the variance of a single distribution of responses selected during a T1-directed episode, whereas at later lags it reflects the variance of two separate distributions. Only when T1 and T2 are sufficiently separated in time, at lags of 400 to 500 ms and longer, is the variance in the equation’s window...
unaffected by T2 reports drawn from an attentional episode directed at T1.

Discussion
From their innovative analysis of errors, Vul, Nieuwenstein, and Kanwisher (2008) concluded that attentional selection is suppressed, delayed, and diffused during the attentional blink. Further, the distinct time courses of these three effects suggested that they reflect different processes. Complex theories of the attentional blink might explain those results, but more parsimonious theories cannot. Here, we reanalyzed data from six attentional blink experiments by fitting a mixture model to response distributions. In contrast to Vul and colleagues’ equation-based approach, our model points to straightforward attentional dynamics, which can be summarized simply: Two attentional episodes cannot occur very close in time.

Our findings are consistent across stimulus categories and types of cue. First, an attentional episode directed at T2 occurs only when the lag between T1 and T2 exceeds 100 to 250 ms. Second, the probability of an episode occurring (efficacy) increases with lag and rises monotonically to reach baseline (i.e., T1 levels) after 600 to 800 ms. Third, episodes at shorter lags are delayed by 75 to 150 ms; latency decreases with increasing lag but remains slightly above baseline at lags beyond 800 ms. Finally, temporal precision is invariant with lag and is statistically indistinguishable from a baseline of around 60 ms. This last observation contributes to evidence that across a variety of tasks and manipulations, the temporal precision for selecting changing stimuli is around 60 to 80 ms (Holcombe & Chen, 2013; Linares, Holcombe, & White, 2009; Martini, 2013; Murakami, 2001).1

Unlike Vul, Nieuwenstein, and Kanwisher’s (2008) equation-based approach, our model-based approach accounts for the effect of items selected during an episode directed at T1 that are reported as T2. It is clear from inspection of response-error distributions that this does occur and that it is more common at shorter lags (see Fig. 2). When T1 and T2 are separated by 500 ms or longer, such occurrences do not impinge on the window of analysis for T2, and both approaches yield similar parameter estimates. However, at shorter lags, the two approaches produce substantially different estimates. It seems that the nonlinearities observed at short lags when data are analyzed using the equation-based approach are an artifact of T2 reports drawn from a T1 attentional episode.2

For our analysis technique to be of use in a particular experiment, that experiment must have two features. First, target items must be distinguished from distractors on the basis of incidental features such as a concurrent cue or a difference in color, rather than by intrinsic differences such as membership of a different category. For example, in one common variant of the attentional blink task, participants identify a target letter embedded in a stream of digits. In this case, they know that the target must be a letter and will not misreport a temporally proximate digit in its place; thus, there is no temporal distribution of errors to analyze. Second, participants must report the identity of a target, not merely indicate its presence or absence, as is sometimes the case.

While we expect that the temporal dynamics reported here generalize to other forms of the attentional blink task, they are undoubtedly moderated by specific task parameters. Error distributions in rapid-serial-visual-presentation tasks differ depending on how the target is defined, such that reporting the color of a target whose identity is specified in advance produces more posttarget errors than when only the category of the target is specified (Botella, 1992; McLean, Broadbent, & Broadbent, 1983). Distributions can differ even between response dimensions within the same task: For example, Botella, Garcia, and Barriopedro (1992) found that reporting the color of an uppercase word embedded in a stream of lowercase words produced more posttarget errors than did reporting its identity. Error distributions are also affected by the statistical distribution of the target position in the stream, such that fixing the position of the target yields more pretarget intrusions than when it varies on each presentation (Martini, 2013). These task- contingent shifts in what we have referred to here as latency, together with the observed temporal symmetry of the position-error distributions, are difficult to reconcile with an online filtering mechanism, such as a cue that triggers the opening of an attentional gate to initiate sampling from the scene. We have instead proposed that, consistent with the spirit of Chun and Potter’s (1995) suggestion that the first selection stage is unaffected by the blink, error distributions reflect sampling from a low-level memory buffer activated by the items even when the cue has not yet occurred (Goodbourn & Holcombe, 2015). It is this stage of persisting activation of item representations that may determine temporal precision, which we found was not affected by the attentional blink.

Although mixture-modeling analysis cannot be applied to cases in which the target-defining feature also defines the report dimension (such as reporting the identity of a letter target among digit distractors), it is well suited to examining how target attributes and response requirements affect selection during the attentional blink. Such analyses of response-error distributions can also be applied to determine, for example, which dimensions of attentional selection improve after practice (Cellini et al., 2015) or which dimensions differ among observers who are more or less susceptible to the attentional blink (Willems, Wierda, van Viegen, & Martens, 2013). We expect that they will provide insights for many of the other research programs that use the attentional blink task.
The reanalysis presented here suggests that what was previously a problematic finding can, in fact, be accommodated by most standard theories of the attentional blink. But one of the central points made by Vul, Nieuwenstein, and Kanwisher (2008) stands: Traditional metrics such as conditional accuracy confound distinct properties of attentional selection in time. Theories of the attentional blink should seek to explain these properties.

**Action Editor**

Ed Awh served as action editor for this article.

**Author Contributions**

P. T. Goodbourn, A. O. Holcombe, and P. Martini developed the study concept. All authors contributed to the study design. Testing and data collection were performed by M. Barnett-Cowan (Western sample), P. Martini (Warwick sample), and I. M. Harris and E. J. Livesey (Sydney sample). P. T. Goodbourn analyzed and interpreted the data and drafted the manuscript. A. O. Holcombe provided critical revisions. All authors approved the final version of the manuscript for submission.

**Acknowledgments**

M. Barnett-Cowan collected the Western sample data as part of the Open Science Collaboration’s Reproducibility Project: Psychology (http://osf.io/eczui/) using experimental code provided by Ed Vul. We thank Ed Vul, Mark Nieuwenstein, and Nancy Kanwisher for providing their data, and Ariella Popple and Dennis Levi for posting their data online.

**Declaration of Conflicting Interests**

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

**Funding**

P. T. Goodbourn and A. O. Holcombe were supported by a grant from the John Templeton Foundation (New Agendas for the Study of Time: Connecting the Disciplines). The present research was also supported by grants from the Australian Research Council (DP110100432 and FT0990767 to A. O. Holcombe).

**Supplemental Material**

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

**Open Practices**

All data and materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/vnkaz/ and https://osf.io/b956g/, respectively. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/25/1/3.full. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/1.%20View%20the%20Badges/ and http://pss.sagepub.com/content/25/1/3.full.

**Notes**

1. For the beginnings of a theory on this topic, see Holcombe (2009) and Goodbourn and Holcombe (2015).
2. Some differences between the two approaches also arise because the model, unlike the equations, accounts for random guessing. However, as Vul, Nieuwenstein, and Kanwisher (2008) noted, adjusting the equation-based approach to correct for guessing yields no qualitative changes to the results.

**References**


