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Conscious perception can be both graded and discrete

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Abstract

The attentional blink (AB) paradigm has been used to address an enduring debate about the nature of conscious perception: does the temporary impairment in conscious perception of the second (T2) of two serially presented targets result from a probabilistic all-or-none loss of information, or does T2 transition into consciousness along a continuum of perceptual fidelity? To investigate this question, we presented noisy orientation patterns as targets embedded in a rapid serial sequence of non-oriented noise distractors, and evaluated perception of T2 orientation using a continuous report paradigm. Using discrete mixture models and variable resource models, we evaluated the effects of manipulating both perceptual and central demands on the precision of T2 responses and the estimated frequency of random guessing. When perceptual competition between targets was emphasized by their sharing of a common visual feature (i.e., orientation), the attentional blink was associated with degraded precision of T2 perception. By contrast, when the task required switching between different attended features across two visually distinct targets, T2 awareness was impaired in an all-or-none manner as evidenced by significant increases in guessing responses. Both statistical and model comparison analyses indicated that loss of target information can be graded or discrete, depending on whether perceptual or higher central stages are taxed by processing demands. Our findings provide new insights into the mechanisms underlying the attentional blink and help reconcile conflicting views regarding how information can be lost from awareness.

Keywords

Attentional Blink; Visual Attention; Awareness; Consciousness; Task Switching

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How do unconscious events transition into our awareness? Studies of the attentional blink (AB) have proven central to the debate that surrounds whether conscious perception emerges discretely or gradually. When participants are presented with a rapid sequence of visual items, the detection and attentional processing of a first target (T1) can severely impair

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Context Statement

Does information arise within conscious perception in an all-or-none fashion or is it gradually formed along a continuum of perceptual fidelity? We directly probed participants to report their exact percept of a target while varying attentional competition at different stages of information processing. Modeling analyses of participants' response errors revealed that graded perception, indexed by precisional loss, occurred when two attended visual targets shared stimulus features. In contrast, changes in guess rate, suggestive of all-or-none perception, occurred when participants had to switch from attending one type of feature to another. These results thereby reconcile the debate about the nature of conscious perception while also providing a mechanistic explanation for why each effect will occur.

the participant's ability to detect or recognize a second target (T2) that follows soon after (Raymond et al., 1992; Chun & Potter, 1995; see Dux & Marois, 2009; Martens & Wyble, 2010 for reviews). The time course of the attentional blink is distinct; the ability to perceive T2 is impaired if it appears soon after T1 (typically 200–500 ms). The ability to perceive T2 gradually recovers from this attentional blink, following the processing of T1, as the temporal lag between T1 and T2 increases. A critical question in the present study is whether this change in T2 accuracy (as a function of lag) occurs because of a gradual refinement of the conscious T2 percept, or because of a change in the probability that T2 will be perceived in an all-or-none fashion.

To address whether conscious perception involves a graded or discrete process, researchers have incorporated subjective measures of T2 visibility in studies of the attentional blink. For instance, Sergent and Dehaene (2004) proposed that a gradual emergence of awareness as the lag between targets increases should lead to a graded distribution of subjective visibility ratings, whereas all-or-none perception of T2 should produce a bimodal distribution of visibility ratings. While their study and subsequent work provided evidence to support discrete models of awareness (Sergent & Dehaene, 2004; Vul, Hanus, & Kanwisher, 2009), others have reported evidence of graded levels of awareness (Nieuwenhuis & de Kleijn, 2011). Discrepancies between these studies have been attributed to the inconsistency of subjective report measures (Cook & Cambell, 1979; Overgaard, Rote, Mouridsen, & Ramsøy, 2006; Ramsøy & Overgaard, 2004), and possible shifts in response criteria (Nieuwenhuis & de Kleijn, 2011). To circumvent the difficulties of determining the validity of subjective ratings, Asplund and colleagues (2014) directly probed participants to report their T2 percept along a continuous circular dimension. They applied a mixture-model analysis (Zhang & Luck, 2008) to estimate the precision of T2 perceptual representations and the proportion of trials that observers made random-guess responses, presumably due to a complete lack of awareness of T2. They found that the AB increased the proportion of T2 guess responses at short lags, without affecting the precision of T2 responses. Their results suggested that the AB disrupts T2 perception in an all-or-none manner, as originally proposed by Sergent and Dehaene (2004). In this context, the AB studies that claimed to find effects of graded perception might be attributed to the vagaries of subjective reports. Here, we considered alternative factors that might account for the divergence in prior findings; namely, might the AB lead to either discrete or graded loss of information about T2 depending on the locus in information processing that is taxed by task demands?

While the AB is known to lead to limitations at late, central stages of information processing (Chun & Potter, 1995; Di Lollo, Kawahara, Ghorashi, & Enns, 2005; Jolicoeur, 1998, 1999; Luck, Vogel, & Shapiro, 1996; Shapiro, Caldwell, & Sorensen, 1998), there is considerable evidence to suggest that the AB can also reflect limitations at earlier stages of perceptual processing (Dux & Marois, 2009; Simione, et al., 2012). Moreover, the processing costs incurred at each stage may be additive (Chun & Potter, 2001). For instance, the AB is magnified by the similarity of T1 and T2, implying that there is an early perceptual contribution to this attentional limitation (Awh, et al., 2004; Landau & Bentin, 2008; Serences, Scolari, & Awh, 2009). From this standpoint, it is noteworthy that Asplund et al.'s study found effects of discrete perception on tasks that likely taxed late rather than early perceptual stages of information processing. Specifically, their tasks relied on categorically distinct targets and required participants to focus on different feature dimensions across T1 and T2 (e.g., T1 luminance versus T2 color-hue, or T1 female face versus T2 male face). While such distinctiveness between targets minimized their confusion, it may also have limited the amount of early perceptual competition between the targets. Reporting distinct properties of T1 and T2 may have necessitated a shift in attentional set to prioritize different features, a process known to induce competition at late central stages of processing (Allport, Styles, & Hsieh, 1994; Di Lollo, Kawahara, Ghorashi, & Enns, 2005; Rubinstein, Meyer, & Evens, 2001).

The present study examined whether T2 perception is necessarily all-or-none, as has commonly been asserted, or whether the quality of T2 perception may vary in a graded manner when greater perceptual competition is induced at early stages of processing. We addressed these questions in a series of experiments that taxed either perceptual or central stages of competition between targets, using noisy orientation patterns as targets presented among non-oriented noise distractors, and measured the perception of T2 orientation using a continuous report paradigm. We evaluated T2 performance by fitting well-known cognitive models, commonly used in studies of visual working memory (Zhang & Luck, 2008; Bays et al., 2009; van den Berg et al., 2012), to characterize the precision of T2 responses and to test for evidence of random guessing responses. Our first set of analyses relied on the mixture model, which contains separate parameters to account for discrete loss of T2 information and graded precision loss (Zhang & Luck, 2008). Our second set of analyses relied on the variable precision resource model, which assumes that some information about the target is always retained and that variability in precision, including trials with vary large errors, can be explained by stochastic fluctuations in the availability of central cognitive resources (van den Berg et al., 2012). Although previous work by Asplund et al. (2014; Supplementary Material) found that the mixture model outperformed the variable precision model in accounting for the distribution of errors caused by the attentional blink, it was important to evaluate whether that would still be the case in the present experimental context.

We hypothesized that the use of task-relevant oriented targets for both T1 and T2 may induce greater perceptual competition between targets due to their shared task-relevant features, which could potentially lead to a graded loss of perceptual precision in the attentional blink. To test this hypothesis, in three experiments we manipulated the degree to which the targets competed at early stages of information processing by varying the degree to which they shared early perceptual and attentional features. We found that the AB led to degraded precision of T2 perception only when attention was divided across stimuli that were visually similar (i.e., both oriented targets; Experiments 1 and 2), irrespective of whether the task required a switch in attentional set or not. Moreover, we found that the variable precision model tended to provide a better fit of behavioral errors than the mixture model under these conditions, consistent with the notion that competition between T1 and T2 led to graded loss of information regarding T2 orientation. These findings can be sharply contrasted with those of Experiment 3 in which T1 and T2 shared no task-relevant features. Here, behavioral errors for T2 orientation were better explained by the discrete mixture model, indicating that the attentional blink led to discrete all-or-none loss of target information when the task required switching between different attended features across visually dissimilar targets.

Taken together, our results provide novel evidence that early-stage competition leads to perceptual degradation of T2 information, whereas competition at late-central stages increases the likelihood of discrete loss of T2 from perceptual awareness. These findings imply that the AB can affect perception in very distinct ways depending on the stage of information processing that is primarily taxed, and provide important new information that can help reconcile conflicting models of conscious perception.

Experiment 1: Is perceptual awareness necessarily discrete?

Experiment 1 investigated whether the AB necessarily leads to a discrete loss of target information. We hypothesized that greater perceptual competition between T1 and T2 at early stages of information processing might induce a graded loss of information about T2. To that end, participants performed a dual task where attention was divided between two oriented target patterns presented within a rapid serial display of noisy non-oriented distractors at varied temporal lags (2, 4, and 9) (Figure 1A). The two targets were presented with distinct colors (see Methods) while the distractors were achromatic. Early perceptual competition was encouraged by varying T1 and T2 along a shared feature – orientation – and requiring subjects to attend to the same feature, thereby minimizing the need to engage central resources to shift between attentional sets. Participants were required to report the precise orientation of T2 at the end of each trial by using a mouse pointer to rotate a central grating, after which they had to make an unspeeded keypress response to indicate whether T1 was rotated clockwise or counterclockwise relative to vertical.

Because the attentional blink fundamentally reveals the transient cost of divided attention (Raymond, Shapiro, & Arnell, 1992; Ward, Duncan, & Shapiro, 1997), we also included a single-task control condition in which participants were instructed to ignore T1 and only had to report the orientation of T2. The inclusion of a single-task control is particularly important for studies such as this one because the perceptual features of T1 might transiently capture some attention even if the target itself is task-irrelevant (Asplund, Fougnie, Zughni, Martin, & Marois, 2014). By comparing the single-task (attend to T2 only) costs of Lag to that of the dual-task (attend to both T1 and T2), we can selectively isolate the limits of voluntary attention on awareness as revealed by the AB (Dux & Marois, 2009).

We evaluated T2 performance by fitting standard versions of the mixture model and variable precision model, and further implemented a variant of each model that allowed for confusion errors between T1 and T2 (Zhang & Luck, 2008; Bays et al., 2009; van den Berg et al., 2012). Given that previous work has reported that the mixture model (with a confusion error parameter) outperforms the variable precision model in accounting for response errors in the attentional blink (Asplund et al., 2014), we focus our first set of analyses on the mixture model. Thereafter, we provide model comparison analyses of the mixture models and variable precision models described above.

Method

Participants.

Fourteen subjects (8 males, 6 females, ages 19–34) with normal or correct-to-normal vision from the Vanderbilt University community provided informed consent and were paid $12 for each of the four 1-hour sessions of participation. The number of participants was determined based on previously reported sample sizes for attentional blink experiments (Asplund et al., 2014). Participants were also awarded a small monetary reward for correct and precise responses, so the maximum performance-based bonus was $6 a session. The Vanderbilt University IRB approved the experimental protocol for this and subsequent experiments.

Two of the fourteen participants were excluded from analysis based on two *a priori* performance criteria. One participant was excluded because their grand averaged T1 accuracy in the dual-task condition fell below 2.5 standard deviations below the grand mean across participants; T1 accuracy in this range yielded too few trials for model estimation and also indicated either inadequate levels of attention directed to the first target or that the calibrated signal-to-noise ratio setting for T1 was too difficult for that participant. Another participant was excluded because their estimated T2 accuracy ($1\text{-}P_{Guess}\text{-}P_{Confusion}$) in the single task at lag 9 fell below 2.5 standard deviations from this condition's mean across participants, thereby signifying improper T2 stimulus calibration or participant inattentiveness in the easiest experimental condition.

Stimuli and Procedure.

All stimuli were generated on a Macintosh computer running MATLAB and the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) and presented on a luminance-calibrated CRT monitor. At the start of every trial, participants were instructed to fixate a gray central dot (0.75º). A keyboard press initiated the rapid serial visual presentation (RSVP) of 22 distractor and 2 target images, presented for 93.33ms each within a circular aperture (8º in diameter) at fixation (see Figure 1A for an example sequence). Distractor images consisted of random gray-scale noise images that were spatial frequency band-pass filtered (1–4 cycles/degree) and presented at 90% contrast. To avoid Gibbs ringing artifacts that can arise from sharp boundaries in the Fourier domain, the 2D filter was convolved with a small Gaussian kernel (10 cycles/degree at full-width half-max) in the Fourier domain.

Target images consisted of a composite of two component images: an oriented sinusoidal grating (2 cycles/degree) and a random bandpass-filtered noise image. The random noise image or weighted composite of the oriented grating and noise image modulated the intensity of each CRT color channel (RGB). The orientation component was presented by specifically modulating the intensity of the red CRT color channel for T1, and the green channel for T2 using a composite template, which comprised the weighted sum of the oriented grating and the noise image (refer to Figure 1a, show examples of the stimuli). Signal and noise in the composite template was scaled with a weighting factor, α, where the target=(oriented grating*α)+noise*(1-α). The weighting factor α was calibrated for each target separately (i.e. separate calibration for α_{T1}, α_{T2}) for each participant and held constant for that observer across test sessions. Calibration relied on a QUEST thresholdestimation procedure (Watson & Pelli, 1983) that measured the observer's performance in pilot runs at discriminating the orientation of a single target stimulus (which varied randomly in orientation, ± 1–89°) as a clockwise or counter-clockwise rotation from vertical, within the RSVP stream, using a target accuracy of 90%. Other color channels (T1: Green/ Blue; T2: Red/Blue) were modulated by the unweighted noise image template so that T1 was more red and T2 was more green. During the main experiment, all possible orientations (0–180º) could be selected for T1 and T2, with the exception of 0º and 90º for T1. The orientations were randomly and independently selected for T1 and T2. T1 was presented in either the fourth, sixth, or eighth serial position in the RSVP stream. The temporal lag between T1 and T2 was manipulated so that T2 could appear as the 2nd, 4th, or 9th item following T1 (187, 373, or 830 ms stimulus onset asynchrony).

Participants performed two different tasks, a single task and a dual task, in separate experimental runs. We focused our investigation on orientation because it is a feature that can be mapped in a continuous circular space, and appears less readily influenced by category-related biases as can occur for color report tasks (Bae, Olkkonen, Allred, & Flombaum, 2015). In both tasks, participants reported the precise orientation of T2, defined by its green color, by adjusting with a mouse pointer the orientation of a central sinusoidal grating that appeared at the end of the trial. Responses were not time-constrained. Positive auditory feedback consisting of a cash register sound associated with a small additional monetary reward (~$0.03 per trial, rounded up to the nearest dollar at the end of the experiment) that was provided for responses within ±10º of the correct orientation.

In the single-task control condition, observers were asked to ignore T1, defined by its red color, and to only perform the T2 discrimination. In the dual task, observers performed the T2 discrimination and also had unlimited time to report the whether the T1 orientation was rotated clockwise or counterclockwise, relative to vertical. While positive feedback and additional monetary reward in the single task only depended on T2 precision, positive feedback in the dual task was contingent on both responding correctly to T1 and making a T2 response within ±10º of the correct orientation. Task order was counterbalanced across participants. Each participant completed a total of 22 experimental runs (54 trials each) resulting in 198 trials/condition across 4 sessions of 1-hour testing.

At the beginning of the experiment, participants completed one practice run for each task (8 trials). After each practice trial, observers also received visual feedback. Visual feedback in both tasks consisted of the presentation of the actual T2 stimulus and a red line corresponding to the reported orientation for 750ms. Feedback in the dual-task practice trials also included the presentation of the correct T1 answer near central fixation.

Analysis.

T1 responses in the dual task were entered into a repeated-measures ANOVA using lag as a within-subjects factor. T2 response errors were calculated on each trial based on the difference between the reported and the correct orientation of the T2 stimulus. Trials with incorrect T1 responses were excluded from T2 analysis (T2|T1 correct).

We analyzed and fitted T2 orientation responses using two different classes of models – the mixture and variable precision models – each with two variants that either did or did not include a confusion error parameter. Thus, the four models assessed were the 2-parameter model (2P Mixture Model; Zhang & Luck, 2008), the 3-parameter mixture model with confusion error (3P Mixture Model, Bays et al., 2009), the variable precision model (Standard VP Model; van den Berg et al., 2012), and the variable precision model with confusion error (VP Model with Confusion; van den Berg et al., 2014). Although more elaborate models have recently been proposed for fitting orientation responses in the context of visual working memory studies (e.g., Pratte et al., 2017; Taylor & Bays, 2018), this study focused on the models above to provide a straightforward approach for comparing two distinct classes of models. We coded and fitted all models based on maximum likelihood estimation using the genetic algorithm available in MATLAB's Global Optimization Toolbox. We confirmed that our approach using the genetic algorithm consistently led to slightly higher (i.e., more likely) log-likelihood scores than existing open-source code made available by other research groups (Bays, Catalao, & Hussain, 2009; Suchow, Brady, Fougnie, & Alvarez, 2013; van den Berg et al., 2012).

For mixture-modeling analysis, we decomposed the distribution of T2 responses as a weighted mixture of either two or three distributions (i.e. 2P or 3P Mixture Model). The first parameter specifies a von Mises distribution centered around the orientation of T2 (Asplund, et al., 2014; Zhang & Luck, 2008), whereas the second parameter specifies a uniform distribution associated with responses uncorrelated with T1 or T2 orientations. The third parameter, implemented in the 3P model, consisted of a von Mises distribution centered around the T1-orientation to account for potential confusion errors, or swapping, between targets (Bays, Catalao, & Hussain, 2009).

For each model evaluation, a separate model was fitted to each participant's T2 response data for each task and lag. The mixture model analysis allowed us to obtain parameter estimates of the precision of T2 responses on successful perception trials, the proportion of T2 random guessing responses (P_{Guess}, associated with height of the uniform distribution), and in the case of the 3P mixture model, the proportion of confusion errors between T1 and T2 ($P_{Confusion}$, proportion of responses attributed to the distribution centered on T1 orientation, assuming the same σ associated with T2).

For our planned statistical comparisons, each parameter of the three-parameter model was then entered into repeated-measures ANOVAs using Task-type and Lag as within-subject factors. The classic AB is defined relative to performance in the single task, reflecting a greater cost of divided attention at the shorter lag than at longer lags that is over-and-above any stimulus salience or masking costs in the single task control (Raymond, Shapiro, & Arnell, 1992; Ward, Duncan & Shapiro, 1997). Thus, of critical interest was whether a significant interaction occurred between Task-type (single versus dual task) and Lag for estimates of σ or P_{Guess}, due to a greater cost of divided attention at the shorter lag than at longer lags.

For the variable precision model, we assumed that the precision of T2 perception could vary from trial to trial, with the kappa parameter of the von Mises stochastically drawn from a gamma distribution (using 1000 samples on each iteration) defined by separate parameters to specify the distribution's shape and scale (van den Berg et al., 2012). In this manner, the probability distribution specified by the VP model can be considered to reflect the weighted sum of a large number of von Mises distributions randomly drawn from a continuous distribution of precision values. The 2P variable precision model required only two free parameters (specifying the shape and scale of the gamma distribution) to fit the T2 response data. The 3P variable precision model (or 3P-VP model) included a third parameter to account for confusion errors centered around T1 and assumed the same distribution of kappa values that was used to account for responses centered around T2.

For model comparison, we calculated the Akaike information criterion (AIC) score of each participant for each model (Akaike, 1974). Lower AIC values indicate a better quality of model fit to the data, while taking model complexity into consideration.

Results

T1 performance in the dual task for this (and subsequent) experiments verified that participants attended to the appropriate feature dimension (see Supplementary analyses). Below, we address how attentional processing of T1 impacted the quality of conscious perception for T2.

Our first set of analyses focused on the 3P mixture model, based on prior work which found that a discrete mixture model with confusion error provided a superior fit of attentional blink response data than other prominent models (Asplund et al., 2014). The 3P mixture model has separate parameters to estimate the likelihood of T2 guessing, the precision of successfully reported T2 percepts, and the likelihood of confusion errors due to erroneously reporting T1's orientation as T2 (Bays, Catalao, & Hussain, 2009). If perception of T2 is discrete and all-or-none in nature, then AB impairments should only lead to increased guessing with no loss of precision on successful perception trials. Alternatively, an AB effect in precision would indicate graded perceptual loss. As alluded to above, an AB effect would be evidenced by a statistical interaction between Task-type (single versus dual task) and Lag (lag 2, 4 and lag 9).

T2 performance

Target Precision.—Target precision was assessed as the standard deviation (σ) of a circular normal distribution fitted to response errors centered around the true T2 orientation. Symptomatic of a dual-task cost on precision, we observed larger σ values – i.e. worse precision – in the dual task compared to the single task, $F(1,11) = 59.1$, $p<0.001$, $\eta^2_{partial} = 0.84$. We also observed a significant effect of Lag, indicating that T2 precision was worse when the two targets appeared more closely in time, $F(2,22) = 10.6$, $p = 0.001$, $\eta^2_{partial} = 0.49$. Critically, there was a significant interaction between Task-type and Lag, $F(2,22) = 4.52$, $p = 0.023$, $\eta^2_{partial} = 0.29$. As seen in Figure 2A and 2B, the dual-task cost in precision was much greater at the shorter lags, indicating that the AB was associated with a degradation in perceptual precision.

Guess Responses.—In contrast to these effects of precision, Task-type had no effect on the proportion of guess responses, P_{Guess}, $F(1,11) = 0.535$, $p = 0.48$, $\eta^2_{partial} = 0.046$. There was, however, a main effect of Lag which revealed fewer guess responses as the lag increased, $F(2,22) = 7.44$, $p = 0.03$, $\eta^2_{partial} = 0.40$. Most importantly, we found no evidence of an interaction between Task-type and Lag for P_{guess}, $F(2,22) = 1.16$, $p = 0.33$, $\eta^2_{partial} = 0.095$, suggesting that the AB was not associated with a change in guess rate.

Contrary to previous claims that the behavioral cost in the AB is solely due to discrete losses in T2 perception (Sergent & Dehaene, 2004; Simione, et al., 2013; Asplund et al., 2014), this experiment demonstrated that the AB can result from an impairment in T2 precision, at least in a task that required attention to be divided to process the same feature across T1 and T2. Moreover, these changes in precision with the AB were unaccompanied by changes in guessing rates, with marginal contributions from confusion errors. These results suggest that the AB can be primarily driven by a graded loss of information about the T2 target.

Confusion Errors.—There was no main effect of Task-type (single vs. dual) on $P_{Confusion}$, $F(1,11) = 1.04$, $p = 0.33$, $\eta^2_{partial} = 0.087$. Confusion errors were, however, more likely to occur at shorter lags than longer lags, $F(2,22) = 10.0$, $p = 0.001$, $\eta^2_{partial} = 0.48$. There was a marginally significant interaction between Task-type and Lag, signifying a potential contribution of $P_{Confusion}$ to the AB, $F(2,22) = 3.18$, $p = 0.061$, $\eta^2_{partial} = 0.22$. Specifically, confusability errors tended to occur with greater frequency at shorter lags than at longer lags under dual-task conditions (Figure 2A and B), suggesting that the AB increased the likelihood that T1 orientation was reported as the T2 stimulus.

Model Comparison Analyses

First, we assessed the standard 2P versions of the mixture model and the variable precision model, focusing on their ability to account for T2 responses in the dual-task lag 2 condition of the attentional blink task. At the group comparison level, the 2P mixture model outperformed the variable precision (VP) model by a small margin (group level $\Delta AIC = 3.0$) and at the individual participant level, provided a better fit in 7 out of 12 cases.

Next, we evaluated the models with confusion error added as a separate parameter, as confusions errors between T1 and T2 orientation were quite prominent at lag 2. Both the 3P mixture and VP models outperformed their 2-parameter model counterparts by a considerable margin (see Table 1), with the 3P-VP model showing a small advantage over the 3P-mixture model (group level $\Delta AIC = 3.7$; participant level, better fit for 7 out of 12 participants), modestly reversing the pattern that was observed for the comparison of the 2P models.

Although the performance of the 3P variable precision model was not so strong as to be decisive, the fact that it provided at least as good of a fit as the 3P mixture model is consistent with the notion that random guessing (or all-or-none loss of information about T2) was not a prominent outcome in this version of the attentional blink. These findings concur with our statistical comparison of performance across lags using the 3P mixture model, which provided novel evidence that the attentional blink can indeed lead to graded loss of T2 information without significantly affecting estimated guess rates. As a whole, the results of the present experiment, in which T1 and T2 consisted of orientation-defined patterns that shared a common visual feature, sharply contrast with previous reports that the AB leads to a selective increase in guessing (Asplund et al., 2014).

Experiment 2: What is the role of attention to similar features?

In Experiment 2, we investigated whether precision degradation in the absence of discrete loss – as was found in Experiment 1 – depended on maintaining the same attentional set to a common visual feature across targets. If so, then requiring a change in the attended feature across T1 and T2 should alleviate the graded loss of T2 precision. The reconfiguration needed to switch attention between distinct features across targets has been previously linked to lower T2 performance, ostensibly by delaying central attentional processing of T2 (e.g. Kawahara et al., 2003, Dale et al., 2013; Dale & Arnell, 2013). Moreover, because task set reconfiguration is thought to involve the disassembling and reassembling of input–output task mappings (Monsell, 1996) and to occur in an all-or-none probabilistic manner (de Jong, 2000; Nieuwenhuis & Monsell, 2002), we surmised that a switch to attend to different perceptual features across targets might induce discrete loss of T2 information.

Participants performed one of three different types of tasks in separate experimental blocks on target stimuli that varied in both color and orientation (Figure 1B). In the no-switch dual task, participants reported the orientation of both targets, thus requiring no switch of attentional priorities in this task. By contrast, in the switch dual task participants had to report the color of T1 but the orientation of T2. We posited that requiring this change in the feature to report would involve attentional task set switching by the participant. Lastly, in a single-task control condition, participants were instructed to ignore T1 and to only report the orientation of T2. In the dual task condition, participants reported the precise orientation of T2 first, and then made a discrimination response regarding the orientation (i.e., clockwise or counterclockwise relative to vertical) or color (i.e., more reddish or greenish) of T1.

Method

Participants.

40 participants (20 male, 20 female, ages 18–35) with normal or corrected-to-normal vision from the Vanderbilt University community provided informed consent and were paid $12 per hour for their participation. Given the medium effect size ($\eta^2_{partial} = 0.08$) in Experiment 1 for the interaction of Task and Lag in guess rate, we ran more participants in Experiment 2 to verify that the absence of an AB in P_{Guess} was not readily attributable to lack of power. Eleven participants were excluded based on the same *a priori* criteria as Experiment 1.

Stimuli and Procedure.

The stimuli and procedures were similar to Experiment 1 with the following exceptions. First, T1 stimuli varied in both orientation and color (see Figure 1B). Specifically, T1 appeared either more reddish or greenish (relative to neutral yellow) on individual trials, whereas T2 was always presented with a distinct bluish hue. Distractors consisted of non-oriented bandpass filtered noise patterns that spatially varied in both their luminance and reddish-greenish hue. Second, participants performed one of three T1 tasks in separate blocks while always reporting the orientation of T2: i) Observers ignored T1 (single-task control), ii) observers categorized the orientation of the T1 stimulus – clockwise or counterclockwise from vertical – thus requiring no switch in attentional set between T1 and T2 (No-switch dual task), iii) reported T1 color (red or green), which required a switch in attentional set from discriminating T1's color to discriminating T2's orientation (Switch dual task). Third, we made an effort to minimize any effects of general task difficulty in discriminating T1 features by requiring each participant to perform an initial QUEST staircase procedure to calibrate the magnitude of the color difference between the two T1 test exemplars. Colors were adjusted in CIE L*a*b color space so that the difficulty of the color categorization task was well matched with the T1 orientation categorization task (~95% accuracy). Fourth, the lag between targets was limited to lags 2 and 9.

Stimuli were constructed in CIE L*a*b color space (L ranging from 18 to 72 centered at a=0, b=0, with a radius of 60) and presented on a luminance- and color-calibrated CRT monitor. The calibration data included the spectra of the monitor RGB primaries at maximum intensity (measured with an Ocean Optics USB4000 spectrometer), as well as the gamma function of each channel (measured with a Minolta LS-110 luminance meter). The monitor's maximum luminance white (CIE (x,y) = 0.3208, 0.3104; luminance = 58.56 cd/m^2) was used as the white point for calculation of CIE L*a*b values.

Distractor images were created by linearly combining separate random bandpass-filtered noise templates (spatial frequency 1–4 cycles/degree) to modulate hue angle between 0–180° from reddish to greenish hue (out of 360°) and to modulate luminance, so that both color and luminance varied independently in the distractor images. The color range of the distractor images was restricted to match the relative target-distractor discriminability in the color dimension with that in the orientation dimension. Like Experiment 1, target stimuli were constructed by first creating a template image consisting of a weighted sum of a component sinusoidal grating (2 cycles/degree) and a band-pass filtered noise image (spatial frequency band-pass filtered 1–4 cycles/degree). The composite template, in Experiment 2, was then used to vary luminance (L in CIE L*a*b) across the T1 stimulus. In each trial, T1 took on one of two colored exemplars (+/− θ in color space), centered around a yellow hue of 90°, rendering it more red or green. Average θ across participants was 32° (SD=19°) and depended on the individual's performance on the QUEST calibration procedure. T2 was a bluish-colored grating whose color did not change throughout the experiment. Its color value of 270° was selected to be distinct from the color range of the distractors and equidistant in hue angle from both of the T1 exemplars.

All three task conditions (i.e. Single task, No-switch dual task, and Switch dual task) required participants to report the precise orientation of T2 with the same method of adjustment as described in Experiment 1, with task conditions performed on separate days and task order randomized across participants. Participants performed 16 experimental runs of each the task, completing a total of 192 trials per condition. At the start of each testing day, observers participated in one practice run (24 trials) of the day's task. Participants also received the same type of feedback as in Experiment 1.

For all three tasks, the distribution of T2|T1 responses in each condition for each participant was fitted separately using the 3-parameter mixture model, and analyzed similarly to Experiment 1. In addition, we performed model comparison by evaluating the mixture and variable precision models as in Experiment 1.

Results

T2 Performance

We performed the 3P mixture-model analysis and first examined the results of the no-switch dual-task condition (relative to the single-task condition), as this condition closely resembled the orientation judgments required for both T1 and T2 in Experiment 1. Generally consistent with the results of the first experiment, comparisons between the no-switch dual task and the single-task control indicated that there were statistically significant interactions between Task-type (no-switch dual and single task) and Lag for both precision ($F(1,28) = 6.7$, $p = 0.015$, $\eta^2_{partial} = 0.19$) and confusion errors ($P_{Confusion}$, $F(1,28) = 4.99$, $p = 0.034$, $\eta^2_{partial} = 0.15$). This pattern of results can be seen in Figure 3A, and in the plots comparing dual versus single task performance in Figure 3B. Also, even with a sample size that was more than twice the size of Experiment 1, we again observed that the interaction between Task-type and Lag was not significant in P_{Guess}, $F(1,28) = 2.3$, $p = 0.14$, $\eta^2_{partial} = 0.077$. While we cannot rule out the possibility that a significant guessing effect might emerge with much larger sample sizes, the present findings are generally consistent with those of Experiment 1, which demonstrated that attending to the orientation of both T1 and T2 led to a loss of precision for T2 with minimal evidence of a change in guess rate.

For the switch-dual task, participants had to shift their attentional set from discriminating T1 color to discriminating T2 orientation. As in earlier comparisons of the no-switch dual-task condition, a directed comparison of the switch dual task and single task revealed statistically significant interactions between Task-type and Lag, indicating an AB effect in precision, $F(1,28) = 15.8$, $p < 0.001$, $\eta^2_{partial} = 0.36$, as well as in $P_{Confusion}$, $F(1,28) = 6.77$, $p = 0.015$, $\eta^2_{partial} = 0.19$. Importantly however, we also observed a significant interaction between Task-type and Lag in P_{Guess}, $F(1,28) = 11.8$, $p = 0.002$, $\eta^2_{partial} = 0.30$, indicating that a switch in attentional set also resulted in a reliable AB effect in guess rate. These findings are more consonant with previous claims that the attentional blink leads to a discrete loss of perception, though even here, we found evidence of a graded loss of T2 information as well.

We also performed direct comparisons between the switch and no-switch dual-tasks. These analyses revealed no significant interaction effects between dual-task types and Lag in either precision or confusion measures, F's < 0.45, p's >0.50, $\eta^2_{partial's} < 0.02$. Although the effect of lag on guessing rate appeared more prominent in the switch-dual task condition than in the no-switch dual task condition (Fig. 3), the interaction between the two dual-task types and lag was statistically marginal, $F(1,28) = 3.86$, $p = 0.06$, $\eta^2_{partial} = 0.12$.

Model Comparison

For model comparison, we evaluated the distribution of behavioral responses in the lag 2 condition for each of the dual tasks (see Table 2). Similar to Experiment 1, we found that the

3P mixture model outperformed the 2P mixture model by a large margin for both no-switch and switch tasks (group level ΔAIC of 341.2 and 381.5, respectively), due to the prevalence of confusion errors. Likewise, the 3P-VP model with confusion error outperformed the standard VP model at fitting both no-switch and switch responses by a similarly large margin (group level ΔAIC of 337.9 and 381.7, respectively).

Direct comparisons between the 3P mixture model and the 3P-VP model indicated a more pronounced advantage for the VP model in this experiment (group level ΔAIC of 18.7 and 65.2 for no-switch and switch tasks, respectively) in comparison to Experiment 1. How should one interpret the better performance of the VP model in this situation, given that the mixture model analysis indicated a significant increase in guessing rate under the dual-task switch condition? One possible interpretation is that the switch dual-task condition induced an increase in errors that greatly deviated from the T2 orientation, but without inducing complete loss of information on individual trials. Another possible interpretation is that both precision loss and increased guessing occurred in this condition, as suggested by the mixture model analysis, but that the degree of precision loss tended to vary from trial to trial, thereby incurring an advantage for the VP model. While we cannot distinguish between these two possible interpretations here, we will see in Expt. 3 that the hybrid pattern of results in this dual-task switch condition can be better understood using a modified paradigm that induces discrete loss of T2 while avoiding loss of precision.

In summary, our original hypothesis in Experiment 2 was only partially borne out. We found that switching between attended features triggered large, if not discrete, loss of target perception with the AB, and that graded loss of T2 precision was observed regardless of whether observers attended to common or different target features across T1 and T2. One interpretation of these results is that graded loss of information dominates the attentional blink, regardless of the locus of competition that is taxed by the AB manipulation. Alternatively, it is possible that participants – either implicitly or explicitly – attended to both the color and orientation of T1 despite instructions to ignore orientation. In retrospect, it seems plausible that participants may have found it beneficial to attend to T1's orientation, given that orientation could provide a useful signal for distinguishing T1 from the non-oriented distractors. The fact that confusion errors between T1 and T2 were more prevalent in both dual-task conditions indicates that some form of competition persisted between T1 and T2. Attention to the same feature (orientation) across the targets might not only have led to T2 precision costs, it might also have mitigated the attentional set switch costs between T1 and T2 in the Switch condition since the participants would already have prepared an orientation template prior to the appearance of T1. For all of these reasons, in Experiment 3 we sought to provide a clearer test of the discrete nature of T2 information loss in the attentional blink by minimizing the possibility of perceptual overlap between T1 and T2.

Experiment 3: What is the role of physical similarity?

The results of Experiment 2 indicated that graded loss of T2 information remains prevalent even when participants must attend to a different task-relevant feature across T1 and T2. What might account for this persistent graded loss in precision when such degradation was not reported in previous studies involving perceptual switches of attention in the AB task (Asplund et al., 2014)?

In Experiment 3, we tested the hypothesis that the perceptual competition between targets, engendered by their physical similarity, is critical for precision loss to occur in the AB. We addressed this question by removing the orientation feature (while retaining the color component) of the T1 stimulus to prevent it from competing with the orientation component of T2. This manipulation has the additional benefit of precluding participants from circumstantially attending to T1's orientation in order to facilitate its selection from distractors. We predicted that with this manipulation, there would be no loss of precision for T2 orientation judgments with the AB, and instead, errors would be manifested by increases in guess rate.

Experiment 3 included two conditions. In the dual-task condition, participants were required to make color discrimination judgments on a non-oriented T1 stimulus and also had to identify and report the precise orientation of a T2 grating (Figure 1C). On separate blocks, they ignored the T1 stimulus and reported T2 orientation in a single-task control condition. Since the T1 stimulus did not have any systematic orientation information, and therefore could not be confused with the orientation of T2, our analyses focused on standard versions of the mixture model and the VP model.

Method

Participants.

Fifteen participants (12 male, 3 female, ages 20–31) with normal or corrected-to-normal vision from the Vanderbilt University community provided informed consent and were paid $12 per hour for their participation. Given the large effect sizes in Experiments 1 and 2 for mixture-model estimates of the AB effect in precision ($\eta^2_{partial} > 0.19$), and in the comparable switch dual-task condition in Experiment 2 for guess rate ($\eta^2_{partial} = 0.28$), we determined *a priori* that this number of participants would provide sufficient power to detect an AB effect should it occur in either measure. We applied the same exclusion criteria here as Experiments 1 and 2. One participant performed very poorly in the T2 single task condition, falling more than 2.5 SD below the group mean performance, and was excluded from our analyses.

Stimuli and Procedure.

Stimulus timing and experimental procedures were similar to Experiment 2, except that we modified the T1 stimulus to minimize perceptual competition between T1 and T2. In Experiment 3, T1 consisted of a non-oriented low spatial frequency target that was constructed using random non-oriented band-pass filter noise (0.3–1.2 cycles/degree) in the luminance domain, with a uniform color component added for the T1 color discrimination task (see Figure 1C). The color composition of T1 was similar to Experiment 2, such that T1 could appear more reddish or greenish, relative to a neutral yellow (90°+/−θ, mean θ = 27.4°). T2 was generated in the same way as in Experiment 2 (composed as a weighted sum of random non-oriented band-pass filtered noise (1–4 cycles/degree) and a sinusoidal grating of 2 cycles/degree), and always presented in the same bluish hue (270° in hue angle) equidistant in color space from each of the two T1 color exemplars. T2 was therefore visually distinct from T1, differing in terms of color, spatial frequency content, and the presence of a systematic orientation signal.

Like Experiment 2, different random bandpass-filtered noise templates were applied to modulate hue angle (0–180°) independently from luminance in the distractor images. To ensure that target-distractor similarity was reasonably well matched in terms of the task-relevant feature for T1 and T2, the color component of the distractor images was varied at a lower spatial frequency (0.3–1.2 cycles/degree, matching the spatial frequency of T1), while the luminance component was varied at a higher spatial frequency (1–4 cycles/degree; matching the spatial frequency changes of T2).

For this experiment, the participants' task was to report the precise orientation of T2 only (single task), or to report the color category of T1 and the precise orientation of T2 (dual task).

Analysis.

Orientation confusion errors between T1 and T2 were impossible given the absence of T1 orientation information. Therefore, we performed our first set of analyses using the standard 2P mixture model and model comparison between the 2P mixture model and the standard VP model. As in previous experiments, T2 responses in the dual tasks were included in model estimation only if they were preceded by correct T1 responses.

Results

T2 Performance

Mixture-model analysis of T2 precision and guess rate revealed a pattern of results in the dual-task condition that appeared entirely distinct from those observed in Experiment 1. As can be seen in Figure 4A and 4B, the dual-task cost in the precision of responses to T2 appeared stable across lags, while the dual-task cost in guess rates appeared much larger at lag 2 than lag 9. Analysis of variance supported these observed trends. Specifically, while there was a main effect of Task-type on σ (single versus dual), $F(1,13) = 13.6$, $p = 0.003$, $\eta^2_{partial} = 0.51$, as well as a main effect of Lag, $F(1,13) = 8.89$, $p=0.01$, $\eta^2_{partial} = 0.41$, but there was also no significant interaction between Task-type and Lag on σ, $F(1,13) = 0.015$, $p = 0.90$, $\eta^2_{partial} = 0.001$, indicating no graded change in T2 precision with the AB.

In contrast, there were not only main effects of Task-type, $F(1,13) = 5.57$, $p = 0.04$, $\eta^2_{partial} = 0.30$, and of Lag on guess rates, $F(1,13) = 6.29$, $p = 0.03$, $\eta^2_{partial} = 0.33$, we also observed a significant interaction between Task-type and Lag on P_{Guess}, $F(1,13) = 7.97$, $p = 0.01$, $\eta^2_{partial} = 0.38$, indicating that the attentional blink led to more frequent guessing at lag 2 than at lag 9. It is worth noting that this AB effect was observed with lag 9 guessing rates that were above 0 (mean = 0.06, SEM = 0.02), making it unlikely that this AB effect in guess rate can be attributed to a floor effect.

These results conform to our prediction that perceptual similarity between targets is a critical factor for inducing the graded loss of T2 information, while a switch in attentional set between visually distinct targets can lead to all-or-none loss of T2 awareness.

Model Comparison

We evaluated the 2P mixture model and standard VP model at fitting behavioral responses associated with the attentional blink at lag 2 in the dual-task condition (see Table 3). This comparison indicated that the 2P mixture model outperformed the VP model by a pronounced margin (group level: ΔAIC = 45.7, participant level: better fit to 8 out of 14 participants). These findings are noteworthy, as they differ from the model comparison results of Experiments 1 and 2, which found either minimal differences in model performance (Exp. 1) or differences that favored the VP model (Exp. 2).

We performed a further test to determine whether participants had likely made guessing responses that bore no relationship to the true orientation of T2. If guessing behavior is indeed present in the distribution of response errors, then a modified VP model that incorporates a parameter to account for a proportion of uniform guessing responses (e.g., Pratte et al., 2017) would be expected to outperform the standard VP model. It should be noted that a VP model with guessing as a specified parameter, while mathematically tractable, deviates from the core assumption that target items are represented along a continuum of precision in a graded manner only. This analysis revealed that the VP model with guessing outperformed the standard VP model (group level ΔAIC = 32.1), though it did not match the performance of the mixture model (group absolute ΔAIC = 13.6). These model comparison results provide strong evidence that discrete loss of T2 information can indeed occur in the attentional blink, when T1 and T2 do not share confusable features and perceptual competition is minimized.

When considering model comparisons across the three experiments, it is interesting to note that the VP model tended to perform better when the targets allowed for featural competition (Expts 1 and 2), whereas the mixture model performed best when the possibility of featural competition was eliminated (Expt. 3). The advantage of the VP model in Experiments 1 and 2 may be attributable to the fact that the AB primarily led to graded loss of precision: if the degree of graded loss tends to vary from trial to trial, this would be expected to confer an advantage to the VP model. The results of Experiments 1 and 2 can be sharply contrasted with those of Experiment 3, in which attending to a non-oriented T1 color target led to a selective increase in guess rate for T2 orientation responses, with no evidence of loss of precision. Under these conditions, the VP model could no longer provide an optimal fit to the distribution of error responses, and the mixture model outperformed the standard VP model.

Discussion

We carried out three experiments aimed at elucidating the nature of target representations in the attentional blink to address a fundamental question about the phenomenology of conscious perception: Is it all-or-none or graded? When observers had to report the orientations of two featurally similar targets (Exp 1), we found that the AB was associated with a graded loss of perceptual precision for T2, with no change in guess rate. In Experiment 2, we replicated these findings of selective loss of precision for T2 when the orientations of T1 and T2 both had to be attended. However, when participants had to report the color of T1 and the orientation of T2 (i.e., attentional switch condition), we observed a hybrid pattern of results – both precision loss and increased guessing were observed. Notably, confusion errors were prevalent even in the attentional switch condition, implying that some form of competition persisted between T1 and T2. In Experiment 3, we used a non-oriented color target to serve as T1, to minimize the possibility of perceptual interference with the oriented T2 target. This experiment revealed a selective increase in guess rate for T2, with no change in T2 precision. Evidence of increased guessing was further borne out by model comparison: the 2P mixture model now outperformed the standard VP model, and a modified VP model with a guessing parameter also outperformed the standard VP model. Thus, the distribution of T2 responses in Experiment 3 are better explained if uniformly distributed responses, that bear no relationship to the target orientation, are incorporated into the model.

Our study demonstrates that target information can be lost in a graded or discrete manner, depending on whether the attentional blink paradigm taxes perceptual or central stages of processing. These findings inform a long-standing debate regarding whether the conscious perception of a target item occurs in a discrete all-or-none manner (Sergent & Dehaene, 2004; Vul, Hanus, & Kanwisher, 2009; Simione, et al., 2012; Asplund et al., 2014) or along a graded continuum of representational quality (Overgaard et al., 2006; Nieuwenhuis & de Kleijn, 2011; Serences, Scolari, & Awh, 2009). When T1 and T2 shared a common visual feature and thereby allowed for greater perceptual competition between targets, we consistently observed evidence of graded loss of T2 precision. By contrast, discrete loss of T2 information occurred when T1 and T2 lacked such common features and thereby minimized perceptual competition. Our findings in Experiment 3 suggest that discrete loss of T2 information results from the central costs of switching attentional task sets between targets.

Importantly, our conclusions are supported by the ensemble of model analyses that we carried out. Instead of relying on a single model, we found that our results are best interpreted with a convergence of models, thus revealing the power of using multiple models in data analysis. Specifically, VP models provided a better fit to the data under conditions that maximized perceptual competition between targets – consistent with a graded loss of T2 precision – whereas the mixture models provided a better fit to the data when the task involved attending to featurally distinct targets – consistent with a discrete loss of T2 perception. That said, we acknowledge that ultimately we cannot discriminate between a response based on zero information from one based on an arbitrarily minute amount of information. Whatever the case may be, it does not negate our main conclusion that perceptual competition predominantly impacts small/graded losses in target perception whereas central competitions triggers massive if not discrete losses of T2 perception.

Our experiments not only distinguish two processing limitations and their impact on visual awareness, they also identify the likely sources of these processing limitations. Specifically, graded and discrete effects of the AB on T2 perception can be reconciled by considering distinct limitations at perceptual and central stages of information processing, a framework that is generally consistent with two-stage models of the AB. While several models explain the AB as a limitation at a late central stage of processing (Bowman & Wyble, 2007; Chun & Potter, 1995; Dux & Marois, 2009; Olivers & Meeter, 2008; Shih, 2008), they also describe an initial perceptual stage of analysis where fleeting representations of each rapidly presented item is created—of distractors and targets alike. These representations require attentional selection for central processing based on their pertinence to behavioral goals, or attentional set, in order to transform them into a durable representation. Without selection, each representation can be overwritten by subsequently presented stimuli (Chun & Potter, 1995; Giesbrecht & Di Lollo, 1998).

How can two-stage models account for loss of T2 precision in the AB? When target stimuli are presented closely in time and share overlapping features, they engage the same feature channels (Awh, et al., 2004) and can elicit competition within the visual system (Potter et al., 2002; Wyble et al., 2011). The interference between target features within these overlapped channels could thus lead to a degradation in T2 representations. It is unlikely, however, that such interference between target representations is limited to the initial stage of perceptual analysis of the AB, prior to attentional selection. Were that the case, lag effects should have been equivalent in the single and dual task versions of the present experiments. Instead, we found that the cost to precision in the dual task was over and above the effect of lag in the single-task control, implying that precision loss of T2 is a consequence of attentionally selecting two physically similar targets that appear closely in time.

As an alternative explanation for loss in T2 precision, it has been suggested that the initiation of an attentional episode to select T1 can impact the temporal precision of the attentional episode for T2, thereby allowing for T2-distractor intrusions (Vul, Nieuwnstein, and Kanwisher, 2009; Goodbourn et al., 2016). According to this account, attending to T1 could result in the summation or swapping of T2 with preceding and subsequent distractors. In the case of categorically defined characters or letters, Vul et al. observed an increased probability of reporting distractors presented before or after T2. But in the case where distractors are not categorically defined, as in the present experiment, we surmise that the surrounding distractors might summate with T2, thereby resulting in a noisier T2 percept and the appearance of a graded cost to perception. This alternative is ruled out by Experiment 3, however, since initiating an attentional episode to T1 did not result in evidence of graded AB costs for T2 despite the fact that distractors still had randomly oriented noise. Therefore, graded AB costs in Experiments 1 and 2 are most likely due to perceptual competition among attended targets that share similar features.

Two-stage models can also account for discrete losses of conscious perception. In Experiment 3, the AB led to a selective increase in T2 guessing with no detectable impact on its precision, replicating work by Asplund et al. (2014) who also required participants to make different judgements on perceptually distinct targets. However, the present study elaborates on this previous work by suggesting a mechanistic source for discrete losses in conscious T2 perception, namely the switch in attentional set. As previously described, stable target representations depend on selection for central processing based on their pertinence to the current attentional set (Chun & Potter, 2001; Di Lollo, et al., 2005;

Giesbrecht & Di Lollo, 1998; Jolicoeur, 1998, 1999; Olivers & Meeter, 2008). If the task necessitates the time-consuming reconfiguration of the attentional set for T2 processing (Allport, Styles, & Hsieh, 1994; Di Lollo, et al., 2005; Dux & Marois, 2009; Giesbrecht & Di Lollo, 1998; Kawahara, et al., 2003; Rubinstein, Meyer, & Evans, 2001; Vachon, Tremblay, & Jones, 2007) and reconfiguration can only take place after T1 selection, there will be a critical time period during which T2 selection will fail. Consequently, a T2 target that appears during this reconfiguration process will be lost. The notion that task set reconfiguration occurs in an all-or-none probabilistic manner (de Jong, 2000; Nieuwenhuis & Monsell, 2002) is entirely consistent with our interpretation that it underlies the discrete failures of T2 perception in the AB.

This is not to say that task set reconfiguration is the only possible account of the attentional blink. Indeed, while some authors consider task set switching as inherent to the AB (Kawahara et al., 2003; Dale et al., 2013; Dale & Arnell, 2013), others view it as giving rise to a separate deficit (Potter et al., 1998; Chun & Potter, 2001; Kelly & Dux, 2011). Clearly, as exemplified in the present study, an AB-like phenomenon can be triggered with or without task set switching (see also Ptito et al., 2008). Moreover, task switching is only one of several possible central processes that have been associated with the AB; others include distractor suppression, cognitive control, attentional deployment and working memory consolidation (Jolicoeur, 1999; see Dux and Marois, 2009; Martens & Wyble, 2010). We do not attempt to adjudicate among different mechanistic definitions of the AB in the present study. Rather, our consideration of the attentional blink can be broadly described as an empirical phenomenon of a deficit in conscious perception for serially presented targets, involving both limitations within visual and central stages of information processing. Clearly, it will be interesting for future studies to determine the extent to which our results are generalizable to the multitude of AB paradigms that have been employed in the field (MacLean & Arnell, 2012) and the extent to which they distinguish between various theories of the AB (Dux & Marois, 2009; Martens & Wyble, 2010).

While our study focused on comparing precision and discrete losses of perception in the attentional blink, it is worth noting that both Experiments 1 and 2 revealed another form of T2 perception error at short lags, namely confusion errors between T1 and T2. Such errors have oftentimes been observed in the AB (Akyürek, et al., 2007; Botella, Barriopedro, & Suero, 2001; Chun, 1997; Raymond, Shapiro, & Arnell, 1992; Spalek, Lagroix, Yanko, & Di Lollo, 2012; Wyble, Bowman, & Nieuwenstein, 2009; Wyble & Swan, 2015), and their origins have mostly been ascribed to errors in binding stimulus features to appropriate temporal events, such that T1 features are perceived to occur at the T2 onset (Akyürek, et al., 2007; Botella, Barriopedro, & Suero, 2001; Chun, 1997; Raymond, Shapiro, & Arnell, 1992; Spalek, Lagroix, Yanko, & Di Lollo, 2012; Wyble, Bowman, & Nieuwenstein, 2009; Wyble & Swan, 2015; but see Spalek, et al., 2012, for an alternative account). The presence of such confusion errors does not impact our interpretation of the origins of graded and discrete losses of target perception in serial processing, nor is it incompatible with extant models of the AB (Chun, 1997; Dux & Marois, 2009, Bowman & Wyble, 2010). Nevertheless, it will be important in future work to incorporate confusion errors with precision and guessing errors in order to develop a holistic understanding of temporal limits to conscious perception in the attentional blink. In that respect, we are intrigued by the idea that precision and guessing errors might correspond to failures of instantiations of proper object type (featural information) and object token (episodic information) during visual perception (Kanwisher, 1991, 1997, Chun, 1997), respectively, with confusion errors referring to the mis-binding of types to their appropriate tokens, a hypothesis that merits further investigation.

In conclusion, our results support AB models suggesting that this deficit in conscious perception does not solely arise from a bottleneck at central stages of processing, but rather, can arise from limitations at multiple stages of information processing (Awh et al., 2004; Chun & Potter, 2001; Dux & Marois, 2009; Serence et al., 2009; Simione, et al., 2012; Wyble & Swan, 2015). More importantly, they also point to limitations of current models of conscious perception by showing that the level of processing at which attentional competition takes place can have distinct consequences on the quality of conscious awareness. Viewed in this context, these conclusions serve to reconcile previously divergent findings in the literature regarding the nature of conscious perception (Asplund et al., 2014; Dehaene, Sergent, & Changeux, 2003; Overgaard, et al., 2006; Nieuwenhuis & de Kleijn, 2011; Sergent & Dehaene, 2004; Vul, Hanus, & Kanwisher, 2009), by demonstrating that visual awareness can be both graded and discrete.

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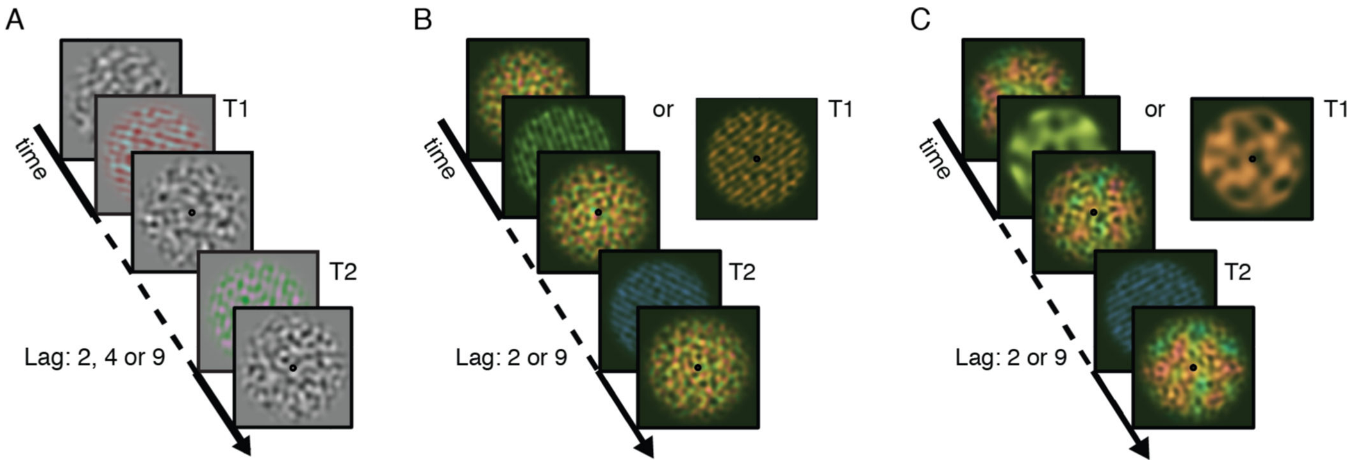

Figure 1. Example stimuli and trial sequences for Experiments 1–3

Each image in the rapid serial display was presented for 93.33ms. A) The dual task in Experiment 1 required reporting the orientation of T1 and T2, which could be distinguished by their color. B) Experiment 2 included two different dual tasks. In the No-switch task, participants reported the orientation of T1 and T2. In the Switch task, they reported the color of T1 and the orientation of T2. T1 varied in color (somewhat reddish or greenish hue) and orientation across trials, whereas T2 (bluish hue) varied only in orientation. Each distractor image was created from two randomly generated non-oriented bandpass-filtered noise patterns, specifying luminance and color variation separately, before their combination. C) In Experiment 3, participants reported the color of T1 and the orientation of T2. Here, the target images were made perceptually distinct: T1 only varied in color across trials and contained no coherent orientation signal, whereas T2 only varied in orientation and was always of the same color.

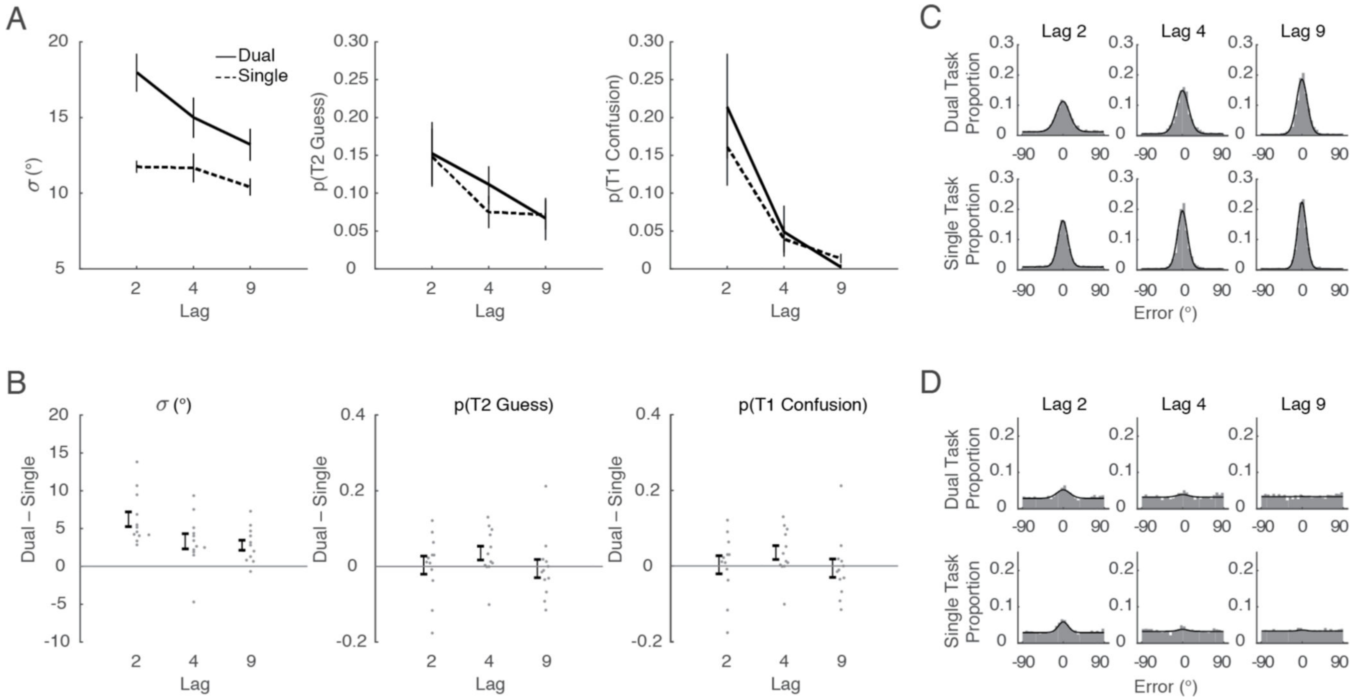

Figure 2. Results from Experiment 1

A) Parameter estimates of the 3-parameter mixture model for T2 response errors plotted as a function of lag for dual and single task performance. Error bars represent ± 1 SEM. B) Dual minus single task performance for each parameter is plotted with error bars as a function of Lag; overlapping data points indicate individual participant parameter estimates. C) Frequency distribution of T2 response errors pooled across participants, plotted by lag and task. The fitted line represents the predicted distribution of errors from the 3P mixture model. D) Distribution of T2 response errors, conditioned on T1 orientation, plotted by lag and task. The fitted line represents the estimated distribution of confusion errors from the 3P mixture model.

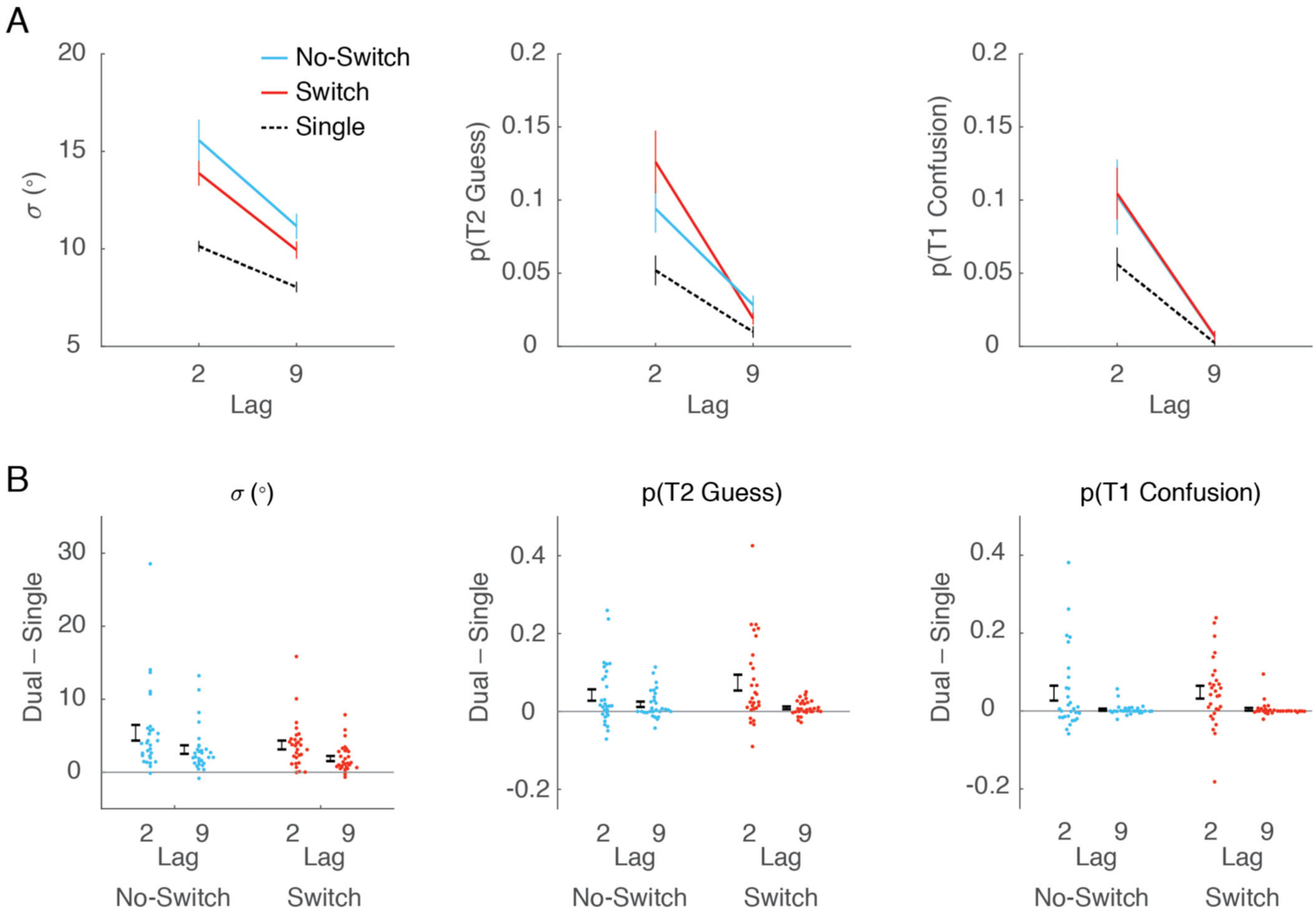

Figure 3. Results from Experiment 2

Parameter estimates of the 3P mixture-model for T2 response errors (A) and dual minus single task performance (B). In different blocks, participants either had to report the color of T1 and orientation of T2 (Switch condition), the orientation of both T1 and T2 (No-Switch condition) or the orientation of T2 only (Single task control).

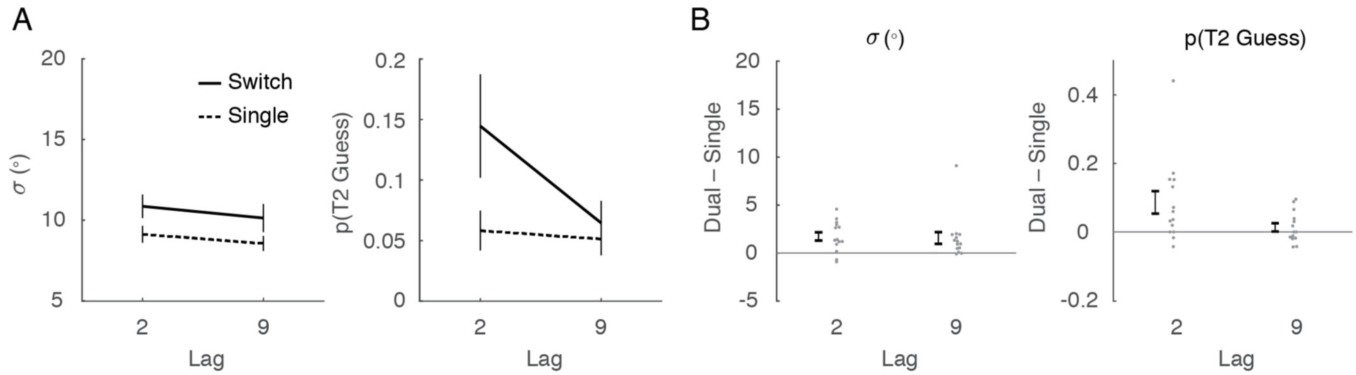

Figure 4. Results from Experiment 3

Parameter estimates of the 3P mixture-model for T2 response errors (A) and dual minus single task performance (B). The dual task required reporting the color of non-oriented target T1 and the orientation of T2; the single task required reporting the orientation of T2 only.

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Table 1

Difference in AIC scores for Experiment 1, shown in comparison to the 3P-VP model. Negative values indicate instances of better fits for a given model. SEM indicates standard error of the mean for ΔAIC scores.

Participant	2P-mixture model	VP model	3P-mixture model
1	28.5	28.2	1.5
2	−3.5	−3.0	−1.4
3	−2.8	−2.0	−0.8
4	37.0	37.0	−0.3
5	32.4	31.0	5.0
6	−3.5	−1.3	−3.0
7	−1.6	−3.8	0.4
8	23.3	23.6	0.2
9	108.3	107.9	2.6
10	8.1	8.6	0.4
11	48.3	49.1	1.4
12	6.7	9.0	−2.3
Sum	281.3	284.3	3.7
Mean	23.4	23.7	0.3
SEM	9.3	9.2	0.6

Table 2

Difference in AIC scores for Experiment 2, shown in comparison to the 3P-VP model.

	No-Switch			Switch		
Person	**2P-Mixture model**	**VP model**	**3P-Mixture model**	**2P-Mixture model**	**VP model**	**3P-Mixture model**
1	1.5	9.2	−4.0	9.9	−1.7	10.5
2	4.6	3.5	1.8	6.8	2.1	4.2
3	19.6	19.0	0.9	3.3	10.8	−2.1
4	47.0	45.8	−0.2	44.8	44.8	1.2
5	4.8	1.8	2.3	16.2	19.6	−0.7
6	1.7	−0.4	1.7	2.3	−1.3	1.1
7	−1.4	−2.0	1.2	16.0	0.3	13.5
8	0.7	−1.9	2.7	0.3	−3.6	1.9
9	7.0	7.9	−1.5	−6.8	−2.5	−4.7
10	56.7	54.9	1.2	20.9	15.5	3.3
11	34.9	35.0	2.6	32.6	35.2	1.7
12	6.2	−2.3	8.2	22.8	5.2	11.8
13	−1.5	−2.0	0.5	−1.2	−0.8	−0.3
14	38.4	38.1	0.8	73.7	67.0	3.2
15	−1.0	−1.9	0.8	5.8	5.6	0.2
16	−8.7	−3.2	−6.6	3.1	−2.7	5.1
17	−0.8	−2.3	1.2	9.5	5.6	2.8
18	4.3	4.2	0.1	0.1	2.6	−2.5
19	69.3	68.2	0.9	18.3	19.1	0.4
20	−1.7	−1.9	0.4	5.3	3.6	1.4
21	27.2	24.4	0.6	12.4	12.1	0.8
22	−2.8	−3.8	−1.6	0.9	0.4	1.1
23	−4.3	−2.0	−2.2	−9.9	−1.0	−8.4
24	0.3	−3.4	2.3	1.5	−4.1	3.5
25	1.3	−2.1	3.3	24.3	21.3	4.8
26	2.8	1.1	1.2	45.8	48.2	4.2
27	14.6	17.1	−1.4	22.9	13.5	5.4
28	23.9	23.8	−0.1	36.5	34.4	1.1
29	15.3	13.1	1.8	28.5	32.2	0.8
Sum	359.9	337.9	18.7	446.7	381.7	65.2
Mean	12.4	11.7	0.6	15.4	13.2	2.2
SEM	3.7	3.6	0.5	3.4	3.4	0.8

Table 3

Difference in AIC scores for Experiment 3, shown in comparison to the 2P-mixture model.

Participant	VP model	VP model with Guessing
1	−6.8	−5.3
2	0.1	0.6
3	−2.3	−1.9
4	17.2	2.0
5	3.2	2.2
6	8.3	2.0
7	−2.4	−0.8
8	1.6	1.0
9	3.4	0.7
10	16.8	1.9
11	8.2	2.1
12	−1.1	1.1
13	−0.2	2.5
14	−0.4	5.4
Sum	45.7	13.6
Mean	3.3	1.0
SEM	1.9	0.7