Psychological Science OnlineFirst, published on January 16, 2014 as doi:10.1177/0956797613513810

Research Report

Psychological Science
201X, Vol XX(X) 1–8

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DOI: 10.1177/0956797613513810
pss.sagepub.com

# The Attentional Blink Reveals the Probabilistic Nature of Discrete Conscious Perception

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**Abstract**

Attention and awareness are two tightly coupled processes that have been the subject of the same enduring debate: Are they allocated in a discrete or in a graded fashion? Using the attentional blink paradigm and mixture-modeling analysis, we show that awareness arises at central stages of information processing in an all-or-none manner. Manipulating the temporal delay between two targets affected subjects' likelihood of consciously perceiving the second target, but did not affect the precision of its representation. Furthermore, these results held across stimulus categories and paradigms, and they were dependent on attention having been allocated to the first target. The findings distinguish the fundamental contributions of attention and awareness at central stages of visual cognition: Conscious perception emerges in a quantal manner, with attention serving to modulate the probability that representations reach awareness.

**Keywords**

attention, consciousness, cognitive processes

Received 5/29/13; Revision accepted 10/30/13

How do the stimuli that engage people's sensory systems rise to the level of conscious perception (Baars, 2005)? Some models view awareness as graded, with the quality of a conscious percept reflecting the amount of sensory information and attention available (Bar et al., 2001; Nieuwenhuis & de Kleijn, 2011; Overgaard, Rote, Mouridsen, & Ramsøy, 2006). Other models, by contrast, posit that although sensory information and attention may be graded, the resulting conscious percept is essentially discrete—either all or none (Dehaene, Changeux, Naccache, Sackur, & Sergent, 2006; Quiroga, Mukamel, Isham, Malach, & Fried, 2008; Vul, Hanus, & Kanwisher, 2009).

This fundamental question has often revolved around the attentional blink (AB) paradigm (Chun & Potter, 1995; Nieuwenstein, Van der Burg, Theeuwes, Wyble, & Potter, 2009; Raymond, Shapiro, & Arnell, 1992), as it clearly implicates central attentional limits to conscious perception (Dux & Marois, 2009). The AB reflects the transient inability to consciously perceive the second of two targets (T2) in a rapid serial visual presentation (RSVP) of distractors when T2 is presented at a short lag (200–400 ms) after the first target (T1). At issue here is whether failures to report T2 occur because no information about that target reaches postperceptual stages of information processing, or because the information is so degraded when it reaches those stages that the conscious representation of the target is inaccurate.

Because standard AB tasks measure discrimination or detection accuracy, they cannot distinguish between these possibilities. To overcome this limitation, recent studies have relied either on inferring probabilistic distributions from multiple guesses (Vul et al., 2009) or on analyzing subjective judgments (Sergent & Dehaene, 2004) to determine whether target perception is all-or-none. However,

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indirect subjective methods, which involve subjects introspecting about how clearly they perceive a target or how confident they are about their perceptual decisions, may be unreliable (Clifford, Arabzadeh, & Harris, 2008; Hannula, Simons, & Cohen, 2005; Seth, Dienes, Cleeremans, Overgaard, & Pessoa, 2008). Moreover, previous approaches have yielded conflicting results, providing evidence both for (Sergent & Dehaene, 2004; Vul et al., 2009) and against (Nieuwenhuis & de Kleijn, 2011; Overgaard et al., 2006) quantal perception in the AB.

To address the issue of whether conscious perception in the AB is discrete, we used a direct and continuous perceptual measure: Subjects reported the quality of their T2 representations by selecting values along a circular dimension of a target feature (e.g., color), and we examined the error distribution of these responses. On trials in which T2 is consciously perceived, a subject's errors will be distributed around the correct value, with the width of the error distribution corresponding to the quality of the T2 percept (narrower distributions imply more precise information). The responses on trials in which T2 is not perceived will be random and uncorrelated with the correct value, so the distribution of response error will be uniform. The observed error distribution can thus be modeled as a mixture of these two component distributions in order to measure the probability that T2 is encoded ($P_e$) and the quality with which T2 is perceived (standard deviation, σ; Anderson & Awh, 2012; Bays, Catalao, & Husain, 2009; Fougnie, Asplund, & Marois, 2010; Zhang & Luck, 2008). If awareness of T2 is all-or-none, then the lag between T1 and T2 should affect the probability that T2 is perceived, but not the precision with which it is perceived. By contrast, if awareness emerges in a graded manner, then an increasingly precise perception of T2 should be established with longer T1-T2 lags.

## Experiment 1: Color AB Task

### *Method*

***Subjects.*** Twenty-eight subjects (13 males, 15 females; ages 18–28 years) from the Vanderbilt University community participated in this study after giving informed consent.[1] The data from 4 additional subjects were removed owing to at-chance T1 performance ($n$ = 3) or extremely poor T2 performance ($n$ = 1).

***Stimuli and procedure.*** The task consisted of reporting the color of two squares presented on a computer monitor in an RSVP stream of colored circles (Fig. 1). A trial began with a centrally presented fixation dot (0.35° × 0.35°) that was followed by an RSVP stream of 10 to 23 colored disks and two square targets (T1 and T2;

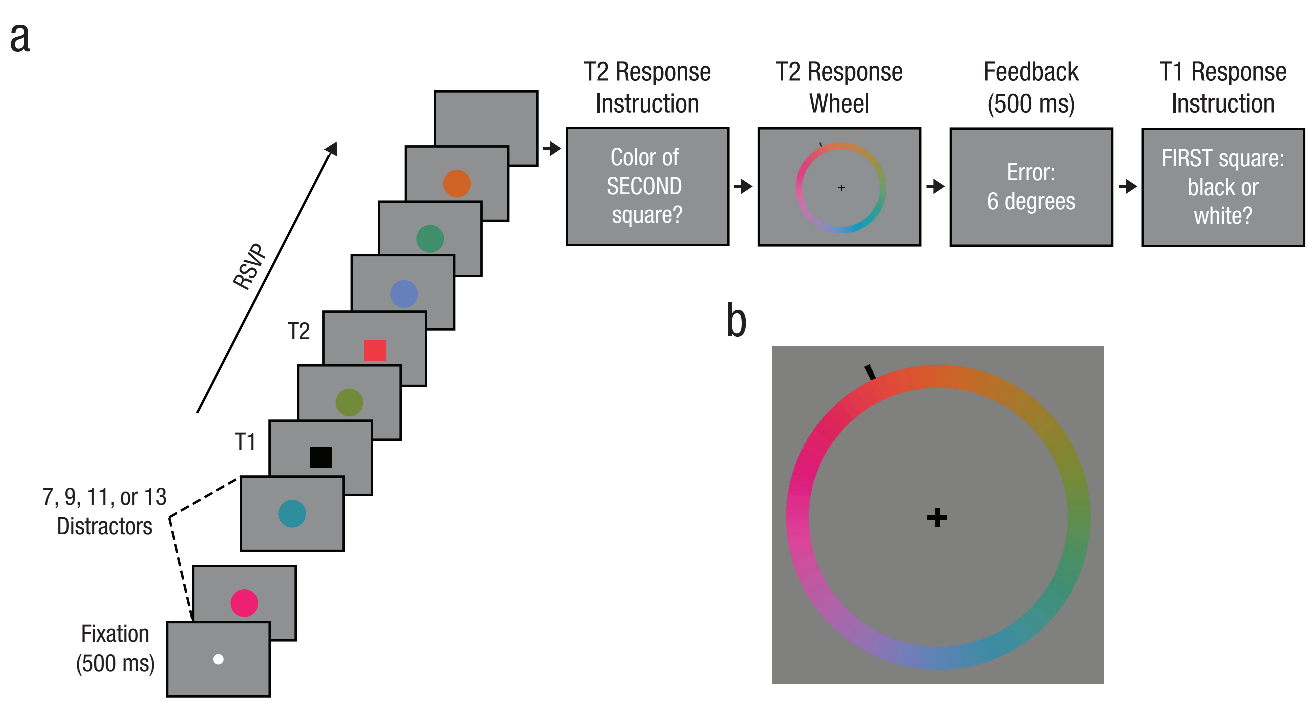


**Fig. 1.** The color attentional blink task (Experiment 1). Two targets (T1, T2) were embedded in a rapid serial visual presentation (RSVP) stream of colored circles (a). Subjects reported the color of T2 using a color wheel (b) and then reported whether T1 was black or white.

2.2° across; Fig. 1a). T1 was either black or white and appeared at serial position 8, 10, 12, or 14. T2 was 1 of 180 equiluminant colors (drawn from *Commission Internationale de l'Éclairage L*a*b** color space, centered at $L = 54$, $a = 18$, $b = -8$, with a radius of 59) and appeared 1, 2, 4, or 8 serial positions (lags) after T1. T2 was always followed by 3 distractor circles that terminated the RSVP stream. Subjects reported the color of T2 by moving the mouse to select 1 of the 180 colors, which were displayed as a color wheel (6.5° radius, 1.1° wide; Fig. 1b). Feedback (error in degrees) was displayed for 500 ms. Subjects then indicated whether T1 was white or black via a key press. Responses were not time restricted.

Prior to the experiment, subjects performed 8 practice trials. The stimulus duration was 190 ms for the first 2 practice trials and 130 ms for the remaining 6 trials. Each subject completed 160 experimental trials in each of four blocks. Stimulus duration for these trials began at 130 ms but was adjusted after every 8th trial to maintain T2 performance near 60% at Lags 1 and 2 (average duration = 115 ms, $SD$ = 10 ms). Specifically, stimulus duration was adjusted (± ≤ 20 ms) based on the number of T2 responses in the preceding 8 trials that were within 45° of their respective targets.

***Analysis.*** Response error was calculated for each trial as the deviation between the target's true color value and the subject's response. Errors were modeled as a weighted mixture of two distributions, with guess responses drawn from a uniform distribution and nonguess responses drawn from a circular normal distribution defined by its mean ($\mu$, a measure of bias) and concentration ($k$, a measure of spread, converted to $\sigma$; Zhang & Luck, 2008). The mixture parameter $P_e$ (relative weight of the circular normal distribution) reflected the probability of encoding T2. The parameter values for each subject and lag condition were computed using maximum likelihood estimation.

As is typical in AB studies, only T2 responses for trials in which T1 was reported correctly (T2|T1) were analyzed. Except for a slight (2°) response bias ($\mu$) at Lag 1, no response bias was detected. Conventional parametric statistical tests were used to assess the effects of lag on $\sigma$ and $P_e$. The strength of evidence for key null effects reported here was also estimated using Bayes factor analysis (see Supplementary Analysis: Bayes Factors in the Supplemental Material available online). Finally, we ensured that a typical AB was observed when response options for T2 were discrete instead of continuous (see Supplementary Experiment 1 in the Supplemental Material).

## Results

Although T1 performance was consistently high regardless of lag (Fig. 2a), a one-way within-subjects analysis of variance revealed that $P_e$ for T2 was sharply affected by lag, $F(3, 81) = 19.85$, $p < .001$. The time course of encoding performance was consistent with the presence of an AB (Fig. 2b). A post hoc $t$ test between the diagnostic AB lag (Lag 2) and a long lag (Lag 8) revealed that $P_e$ was lower at Lag 2, $t(27) = 7.29$, $p < .001$ (see Fig. 3 for aggregated response-error data). Moreover, $P_e$ was higher at Lag 1 than at Lag 2, $t(27) = 2.94$, $p < .01$, a well-known

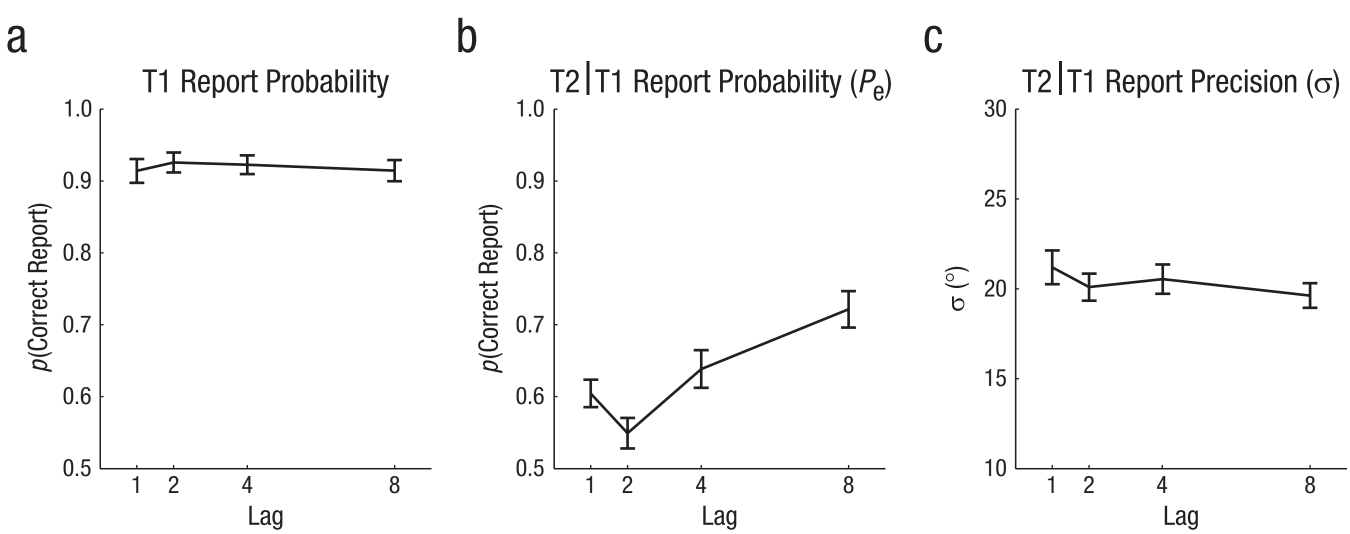


**Fig. 2.** Results for the color attentional blink task (Experiment 1): (a) probability of correct report of the first target (T1) as a function of the lag between T1 and the second target (T2), (b) probability of T2 encoding ($P_e$) as a function of T1-T2 lag, and (c) precision of T2 encoding ($\sigma$) as a function of T1-T2 lag. Note that lower $\sigma$ values (standard deviation of report error) correspond to better precision. The results for T2 were calculated using data only from those trials in which T1 was reported correctly (T2|T1). Error bars represent standard errors of the mean.

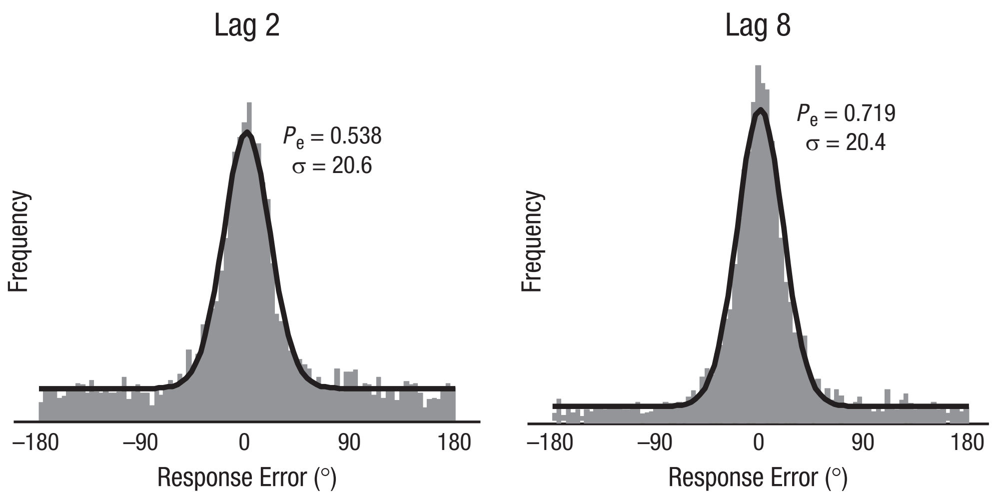


**Fig. 3.** Distribution of response errors for the second target (T2) in the color attentional blink task (Experiment 1), aggregated across all subjects separately for Lags 2 and 8. Each distribution was modeled (black line) as a mixture of two distributions, with nonguess responses drawn from a circular normal distribution and random guesses drawn from a uniform distribution. $P_e$ = probability of T2 encoding; σ = precision of T2 encoding (in degrees).

feature of the AB known as Lag-1 sparing (Raymond et al., 1992; Visser, Zuvic, Bischof, & Di Lollo, 1999). Unlike $P_e$, σ for T2 was barely affected by lag, $F(3, 81) = 2.27$, $p = .09$ (Fig. 2c). That marginal effect cannot account for the AB, however, as σ was no greater at Lag 2 than at Lag 8, $t(27) = 0.34$, $p = .73$. Instead, the marginal effect appears to have been driven by higher σ at Lag 1 than at Lag 2, $t(27) = 1.87$, $p = .07$, perhaps because the high contrast of T1 affected precision of encoding T2. A follow-up experiment ruled out the possibility that T2 perception was too impoverished for effects on σ to be observed, as the same pattern of results was obtained when $P_e$ was above 80% at short lags (see Supplementary Experiment 2 in the Supplemental Material).

## Experiment 2: Face AB Task

Does the quantal nature of conscious perception found in Experiment 1 generalize to other stimulus classes and AB paradigms? Color stimuli contain little information and can be fully encoded in 50 ms (Todd, Han, Harrison, & Marois, 2011; Vogel, Woodman, & Luck, 2006). It is possible that lag effects on the precision of T2 encoding emerge only when stimuli are presented too briefly to be fully encoded, so that attention can play a role in increasing the amount of information that is extracted from T2. In addition, the results of Experiment 1 may have been tied to the specific structure of the task, in which the feature to be reported (color) was distinct from that used to identify T2 (shape).

To address these issues in Experiment 2, we used faces as targets, as faces are complex stimuli that take several hundred milliseconds to be fully encoded (Curby & Gauthier, 2007; Eng, Chen, & Jiang, 2005; Todd et al., 2011). Furthermore, instead of an RSVP design, we used a skeletal AB paradigm (Ward, Duncan, & Shapiro, 1996): The only stimuli were the two face targets (and surrounding masks), which allowed for straightforward selection of the T2 stimulus (Fig. 4). Two parameters were manipulated across trials: the stimulus onset asynchrony (SOA) of T1 and T2, which was either short (200 ms) or long (800 ms), and the duration of T2, which was either 100 or 200 ms. The latter manipulation provided a built-in control for assessing the sensitivity of the mixture-modeling analysis to detect changes in precision, as variations in stimulus duration modulate the amount of information extracted (e.g., Todd et al., 2011). Moreover, as AB effects are attenuated at longer stimulus durations (Reeves & Sperling, 1986), one would expect a much weaker AB with the 200-ms stimulus duration.

### *Method*

***Subjects.*** There were 16 subjects (6 males, 10 females; ages 19–28 years). Four additional subjects were excluded because their T1 performance was at chance ($n = 2$) or their T2 report accuracy was too low ($P_e$ < 10%, $n = 2$) for us to calculate reliable precision estimates (Anderson & Awh, 2012).

***Stimuli and procedure.*** Each trial consisted of the serial presentation of two masked face targets for subsequent report (Fig. 4a). T1 was one of two female faces, T2 was a face chosen from a pseudocontinuous stimulus space of 3 faces and 147 morphs between them, and the masks were mosaic scrambles of these faces.

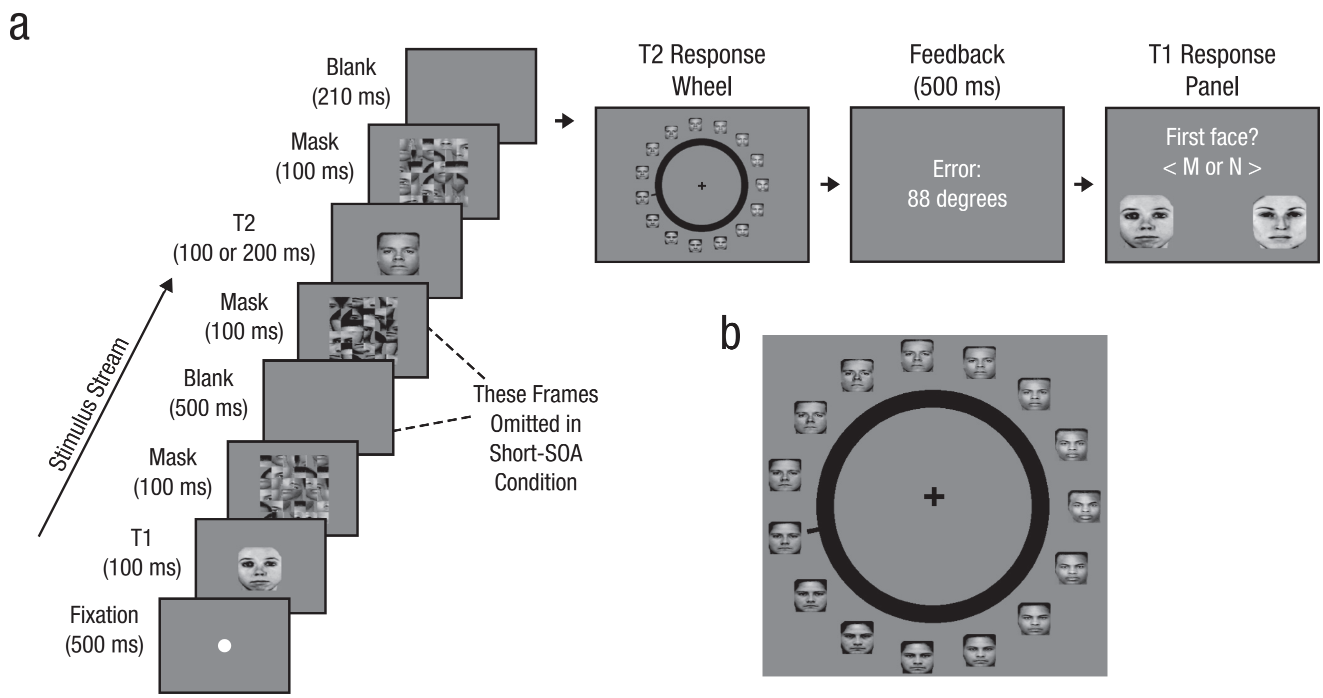


**Fig. 4.** The face attentional blink task (Experiment 2). As illustrated in (a), two masked faces (T1, the first target; T2, the second target) were presented sequentially with either a short (200 ms) or a long (800 ms) stimulus onset asynchrony (SOA). Subjects used a face wheel (b) to report the identity of T2 and then reported which of two faces had been presented as T1.

To construct the morphed faces, we chose three highly distinct male faces as anchors and constructed a linear progression of 49 morphs between each pair of anchor faces using Norrkross MorphX (Norrkross Software, http://www.norrkross.com). Each target face subtended 4.2° × 4.2°. The scrambled faces (6.3° × 6.3°) were created by dividing a given morphed face into 16 tiles and randomly selecting the tiles with replacement to form a 6 × 6 grid.

A trial began with the presentation of a fixation dot, followed by T1 (100 ms), and then a scrambled face (100 ms) that served as a backward mask (Fig. 4a). In the short-SOA condition (200 ms), T2 and its backward mask immediately followed T1's mask. In the long-SOA condition (800 ms), T1's mask was followed by a blank (500 ms), after which scrambled faces immediately preceded and followed T2. These sequences ensured that T2 was equally masked in the two SOA conditions because the T1 backward mask in the short-SOA condition also served as a forward mask for T2. The manipulations of SOA and T2 duration were fully crossed. To prevent subjects from focusing on specific locations in each face, we jittered each stimulus's position by up to 0.7°.

A probe face wheel appeared 210 ms after presentation of the T2 mask. Fifteen 2.0° × 2.0° faces (equally separated in the physical and morph space used to create the stimuli) appeared around the 11.9° wheel (Fig. 4b). Subjects used a computer mouse to move a black indicator until it pointed to the perceived T2 face or a mental interpolation between two adjacent faces. Feedback on the response error (in degrees) was provided for 500 ms. Finally, a display ("First face?") prompted subjects to indicate by button press which of the two female faces had been presented as T1. Subjects practiced on 8 trials before completing four blocks of 160 trials each.

Supplementary Experiment 3 confirmed that a standard AB could be observed with the skeletal design and face stimuli, whereas Supplementary Experiment 4 confirmed that these effects were largely due to attending to T1 (see the Supplemental Material for details on these experiments).

## *Results*

T1 accuracy, as well as $P_e$ and σ for T2, were submitted to two-way within-subjects analyses of variance with factors of SOA and T2 duration. T1 accuracy showed only a small effect of SOA, $F(1, 15) = 16.22$, $p = .001$ (Fig. 5a). For $P_e$, the SOA × T2 Duration interaction was significant, $F(1, 15) = 13.82$, $p = .002$. $P_e$ was markedly reduced when the SOA and T2 duration were both short (Fig. 5b), which is the condition expected to produce an AB. In contrast, σ neither was affected by SOA, $F(1, 15) = 0.02$, $p = .88$, nor exhibited an interaction between SOA and T2

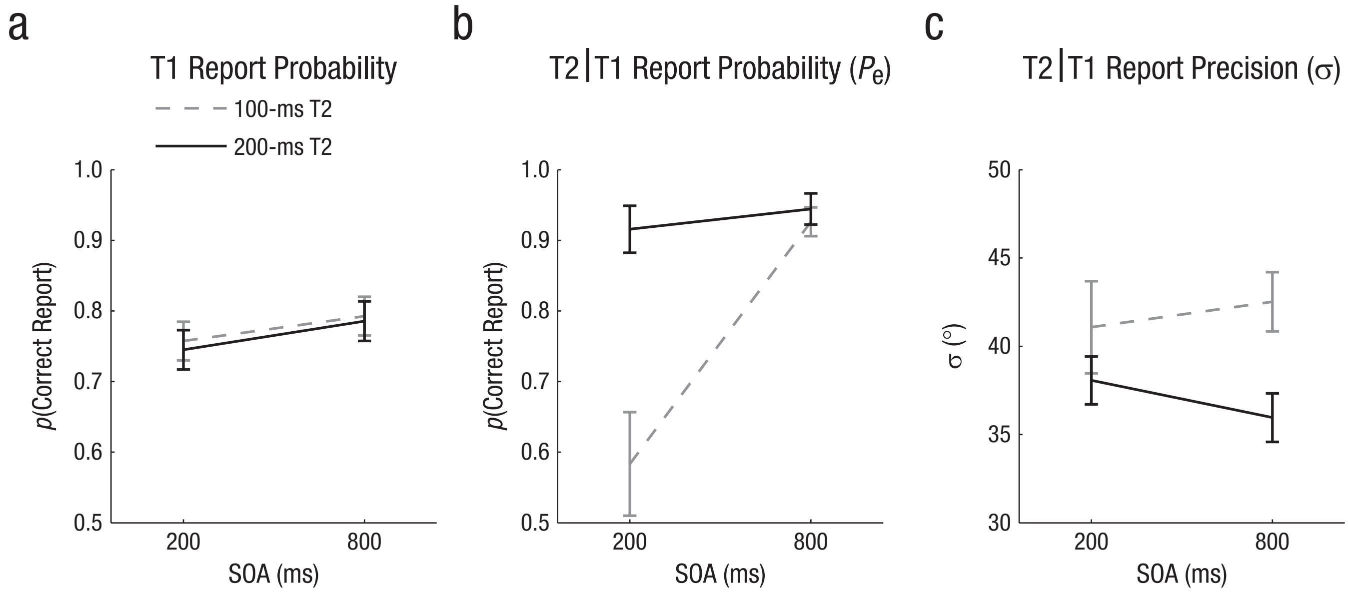


**Fig. 5.** Results for the face attentional blink task (Experiment 2): (a) probability of correct report of the first target (T1) as a function of stimulus onset asynchrony (SOA) between T1 and the second target (T2), (b) probability of T2 encoding ($P_e$) as a function of SOA, and (c) precision of T2 encoding (σ) as a function of SOA. Note that lower σ (standard deviation of report error) values correspond to better precision. In each graph, results are shown separately for trials on which T2 was presented for 100 ms and trials on which T2 was presented for 200 ms. The results for T2 were calculated using data only from those trials in which T1 was reported correctly (T2|T1). Error bars represent standard errors of the mean.

duration, $F(1, 15) = 0.70$, $p = .41$ (Fig. 5c). This parameter was, however, strongly modulated by T2 duration, $F(1, 15) = 11.11$, $p = .005$, which indicates that the mixture-modeling analysis was sensitive to the precision at which a stimulus was encoded; doubling T2 duration should allow more information to be extracted and yield a more veridical face representation (Todd et al., 2011). As in Experiment 1, the strength of evidence for the key null effects was supported by Bayes factor analysis (see Supplementary Analysis: Bayes Factors in the Supplemental Material).

Consistent with the results from Experiment 1, these findings suggest that the deficit in conscious target perception resulted solely from a change in the probability of encoding targets rather than from a modulation of the precision of target representations.

## Discussion and Conclusions

Across both stimulus classes (colors and faces) and experimental designs (RSVP and skeletal), we found that the reported precision of a target item is not affected in the AB, even though our paradigms had the sensitivity to detect such effects. Moreover, when we fit the data with an alternative variable-precision model that assumes that guesses are targets encoded at very low precision (van den Berg, Shin, Chou, George, & Ma, 2012; see also Fougnie, Suchow, & Alvarez, 2012), we found that our original model with distinct guess and precision parameters better accounted for the data (see Supplementary Analysis: Variable Precision Model in the Supplemental Material). Finally, whereas precision judgments were made on the basis of consciously reported targets, guesses were not (see Supplementary Experiment 5 in the Supplemental Material). Although we cannot exclude the possibility that nonreported targets reached awareness but were immediately forgotten, together our results clearly support the hypothesis that conscious perception, at least at central stages of information processing, is all-or-none (Dehaene et al., 2006; Sergent & Dehaene, 2004).

Given that the AB results from the costs of attentional deployment to T1 (Supplementary Experiment 4; Dux & Marois, 2009), our findings also indicate that attention modulates the probability of a quantal episode of conscious perception. This account, however, does not rule out qualitative attentional effects at earlier stages of visual information processing (e.g., perceived contrast; Liu, Abrams, & Carrasco, 2009; Reynolds & Chelazzi, 2004). Instead, it suggests that under conditions in which stimuli compete for representation at postperceptual stages of information processing, attention regulates the probability of all-or-none conscious representations of task-relevant events without affecting the precision of these representations.

### Author Contributions

R. Marois developed the study concept. R. Marois, C. L. Asplund, and D. Fougnie contributed to the study design. C. L. Asplund, D. Fougnie, S. Zughni, and J. W. Martin collected data, and C. L. Asplund, D. Fougnie, and S. Zughni analyzed data. R. Marois

and C. L. Asplund drafted the manuscript, and all authors contributed to, and approved, the final version.

## Acknowledgments

We thank Ellie Conser for experimental assistance.

## 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

This work was supported by National Institute of Mental Health Grant RO1 MH70776 to R. Marois and by National Eye Institute Grant P30-EY008126 to the Vanderbilt Vision Research Center.

## Supplemental Material

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

## Note

1. Vanderbilt's institutional review board approved the protocol for all experiments.

## References

Anderson, D. E., & Awh, E. (2012). The plateau in mnemonic resolution across large set sizes indicates discrete resource limits in visual working memory. *Attention, Perception, & Psychophysics*, *74*, 891–910. doi:10.3758/s13414-012-0292-1

Baars, B. J. (2005). Global workspace theory of consciousness: Toward a cognitive neuroscience of human experience. *Progress in Brain Research*, *150*, 45–53.

Bar, M., Tootell, R. B., Schacter, D. L., Greve, D. N., Fischl, B., Mendola, J. D., . . . Dale, A. M. (2001). Cortical mechanisms specific to explicit visual object recognition. *Neuron*, *29*, 529–535.

Bays, P. M., Catalao, R. F. G., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, *9*(10), Article 7. Retrieved from http://www.journalofvision.org/content/9/10/7.full

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

Clifford, C. W. G., Arabzadeh, E., & Harris, J. A. (2008). Getting technical about awareness. *Trends in Cognitive Sciences*, *12*, 54–58. doi:10.1016/j.tics.2007.11.009

Curby, K. M., & Gauthier, I. (2007). A visual short-term memory advantage for faces. *Psychonomic Bulletin & Review*, *14*, 620–628.

Dehaene, S., Changeux, J. P., Naccache, L., Sackur, J., & Sergent, C. (2006). Conscious, preconscious, and subliminal processing: A testable taxonomy. *Trends in Cognitive Sciences*, *10*, 204–211.

Dux, P. E., & Marois, R. (2009). The attentional blink: A review of data and theory. *Attention, Perception, & Psychophysics*, *71*, 1683–1700. doi:10.3758/APP.71.8.1683

Eng, H. Y., Chen, D., & Jiang, Y. (2005). Visual working memory for simple and complex visual stimuli. *Psychonomic Bulletin & Review*, *12*, 1127–1133.

Fougnie, D., Asplund, C. L., & Marois, R. (2010). What are the units of storage in visual working memory? *Journal of Vision*, *10*(12), Article 27. Retrieved from http://www.journalofvision.org/content/10/12/27.full

Fougnie, D., Suchow, J. W., & Alvarez, G. A. (2012). Variability in the quality of visual working memory. *Nature Communications*, *3*, Article 1229. Retrieved from http://www.nature.com/ncomms/journal/v3/n11/full/ncomms2237.html

Hannula, D. E., Simons, D. J., & Cohen, N. J. (2005). Imaging implicit perception: Promise and pitfalls. *Nature Reviews Neuroscience*, *6*, 247–255.

Liu, T., Abrams, J., & Carrasco, M. (2009). Voluntary attention enhances contrast appearance. *Psychological Science*, *20*, 354–362. doi:10.1111/j.1467-9280.2009.02300.x

Nieuwenhuis, S., & de Kleijn, R. (2011). Consciousness of targets during the attentional blink: A gradual or all-or-none dimension? *Attention, Perception, & Psychophysics*, *73*, 364–373. doi:10.3758/s13414-010-0026-1

Nieuwenstein, M., Van der Burg, E., Theeuwes, J., Wyble, B., & Potter, M. (2009). Temporal constraints on conscious vision: On the ubiquitous nature of the attentional blink. *Journal of Vision*, *9*(9), Article 18. Retrieved from http://www.journalofvision.org/content/9/9/18.full

Overgaard, M., Rote, J., Mouridsen, K., & Ramsøy, T. Z. (2006). Is conscious perception gradual or dichotomous? A comparison of report methodologies during a visual task. *Consciousness and Cognition*, *15*, 700–708.

Quiroga, R. Q., Mukamel, R., Isham, E. A., Malach, R., & Fried, I. (2008). Human single-neuron responses at the threshold of conscious recognition. *Proceedings of the National Academy of Sciences, USA*, *105*, 3599–3604. doi:10.1073/pnas.0707043105

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of Experimental Psychology: Human Perception and Performance*, *18*, 849–860.

Reeves, A., & Sperling, G. (1986). Attention gating in short-term visual memory. *Psychological Review*, *93*, 180–206.

Reynolds, J. H., & Chelazzi, L. (2004). Attentional modulation of visual processing. *Annual Review of Neuroscience*, *27*, 611–647.

Sergent, C., & Dehaene, S. (2004). Is consciousness a gradual phenomenon? Evidence for an all-or-none bifurcation during the attentional blink. *Psychological Science*, *15*, 720–728.

Seth, A. K., Dienes, Z., Cleeremans, A., Overgaard, M., & Pessoa, L. (2008). Measuring consciousness: Relating behavioural and neurophysiological approaches. *Trends in Cognitive Sciences*, *12*, 314–321.

Todd, J. J., Han, S. W., Harrison, S., & Marois, R. (2011). The neural correlates of visual working memory encoding: A time-resolved fMRI study. *Neuropsychologia*, *49*, 1527–1536. doi:10.1016/j.neuropsychologia.2011.01.040

van den Berg, R., Shin, H., Chou, W. C., George, R., & Ma, W. J. (2012). Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences, USA*, *109*, 8780–8785.

Visser, T. A., Zuvic, S. M., Bischof, W. F., & Di Lollo, V. (1999). The attentional blink with targets in different spatial locations. *Psychonomic Bulletin & Review*, *6*, 432–436.

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2006). The time course of consolidation in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *32*, 1436–1451.

Vul, E., Hanus, D., & Kanwisher, N. (2009). Attention as inference: Selection is probabilistic; responses are all-or-none samples. *Journal of Experimental Psychology: General*, *138*, 546–560. doi:10.1037/a0017352

Ward, R., Duncan, J., & Shapiro, K. (1996). The slow timecourse of visual attention. *Cognitive Psychology*, *30*, 79–109.

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*, 233–235.

DOI:10.1177/0956797613513810

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## Supplementary Material

### Supplementary Analysis: Bayes factors

We employed Bayes factor (BF) analyses (Rouder et al., 2009) to determine the ratio of evidence in favor of the null hypotheses (no $P_e$ or σ differences) and of the alternative hypotheses for our pair-wise comparisons of interest. We report the inverse of this value, meaning that large numbers indicate substantial evidence for a $P_e$ or σ effect, whereas small numbers indicate substantial evidence for the no such effect. (A value of 1 would indicate equal evidence in favor of and against the null.) For example, in Expt. 1, the alternative hypothesis that $P_e$ was affected by lag was $2.2 \times 10^5$ times more likely than the null, whereas the inverse BF of 0.154 for σ indicates that the the null hypothesis of no effect of lag on σ was 6.5 times more likely than the alternative hypothesis (Supplementary Table 1).

| | $P_e$ | | σ | |
|---|---|---|---|---|
| Experiment | Statistic | Inverse BF | Statistic | Inverse BF |
| Expt. 1: Color AB | | | | |
| **Lag 2 vs. Lag 8** | $\mathbf{t_{27} = 7.29}$ | $\mathbf{2.20 \times 10^5}$ | $\mathbf{t_{27} = 0.34}$ | **0.154** |
| Expt. 2: Face AB (Report T1) | | | | |
| Main effect of SOA | $F_{1,15} = 15.86$ | 32.8 | $F_{1,15} = 0.02$ | 0.191 |
| Main effect of Duration | $F_{1,15} = 30.06$ | 480 | $F_{1,15} = 11.11$ | 10.0 |
| **Interaction** | $\mathbf{F_{1,15} = 13.82}$ | **20.2** | $\mathbf{F_{1,15} = 0.70}$ | **0.262*** |
| Supp. Expt. 4: Face AB (Ignore T1) | | | | |
| Main effect of SOA | $F_{1,15} = 3.86$ | 0.981 | $F_{1,15} = 0.01$ | 0.190 |
| Main effect of Duration | $F_{1,15} = 7.59$ | 3.57 | $F_{1,15} = 16.27$ | 36.1 |
| **Interaction** | $\mathbf{F_{1,15} = 8.40}$ | **4.59** | $\mathbf{F_{1,15} = 1.32}$ | **0.347*** |
| Meta-analytic result | | $3.93 \times 10^8$ | | 0.0607 |

**Supplementary Table 1**. Statistical results and inverse Bayes factors (BF) for key comparisons. Values for single comparisons were found using the calculators available at http://pcl.missouri.edu/bf-one-sample . For the Bayes factor meta-analysis, comparisons in bold were aggregated using the method of Rouder & Morey (2011), with directional hypotheses that $P_e$ would be reduced and σ increased at short lags (or short SOA when T2 duration was short). Asterisks indicate non-significant differences that went against these directional alternative hypotheses.

DOI:10.1177/0956797613513810

## Supplementary Experiment 1: Standard color AB task

The purpose of this experiment was to verify that the color AB task used in the mixture modeling experiment yielded a standard AB when the T2 probe was discrete, as is typical for an AB task.

### Method

*Participants*

Eleven subjects (4 males; age range 18 - 31 years) from the Vanderbilt University community participated in this study. The data from three additional participants were excluded due to performance indistinguishable from chance.

Stimuli and Procedure

The experimental design closely resembled the procedures illustrated in Fig. 1 of the main text except that participants reported T2's color from a set of four possible values rather than from a continuous spectrum on a color wheel. T2 appeared in the RSVP stream at 1, 2, 4, 6, 8 or 10 serial positions after T1. T2's color was randomly chosen from a set of four distinct values, which were selected from evenly spaced intervals on the color wheel space: (246, 37, 111), (182, 114, 19), (64, 143, 112) or (140 117, 190) (all RGB values). T2 was always followed by three distractors to terminate the RSVP stream. Text displaying 'Color of SECOND square?' prompted participants to press the numerical key (1-4) associated with the color they saw. The identifying colors appeared on the four keys. After the T2 response, text reading 'First square: WHITE or BLACK?' prompted subjects to report T1's color with a keypress: '<' for white or '>' for black. Finally, a blank gray screen appeared for 200 ms after the T1 response and a new trial initiated. Responses to probes were not time-restricted. Note that the order of target responses, which is reversed from the pattern in a typical AB experiment, was adopted here to match the order of response of the mixture modeling experiment (Experiment 1). As shown below, an AB still occurs even with this reversal of response order.
The duration of each stimulus frame in the RSVP began at 130 ms but was then individually adjusted with performance (the average stimulus duration was $139 \pm 7$ ms.). A staircase procedure maintained subjects' T2 performance between 50% and 75% for lags 1 and 2 and restricted its range to 43-260 ms. Furthermore, the spatial position of each object in the RSVP was slightly jittered around the screen center to prevent perceptual fusion of the stimuli (and hence target squares to easily pop out). The amount of jitter was chosen independently in the x and y directions from a uniform distribution between -0.2 and 0.2 $^{\circ}$ of visual angle from the screen center.

Each subject participated in a total of 240 trials (2 blocks of 120 trials). Immediately preceding the experimental session, subjects received written and oral instructions, as well as performed a short practice session comprised of six trials. On the first two practice trials, each item in the RSVP was displayed for 200 ms, which then decreased to 130 ms.

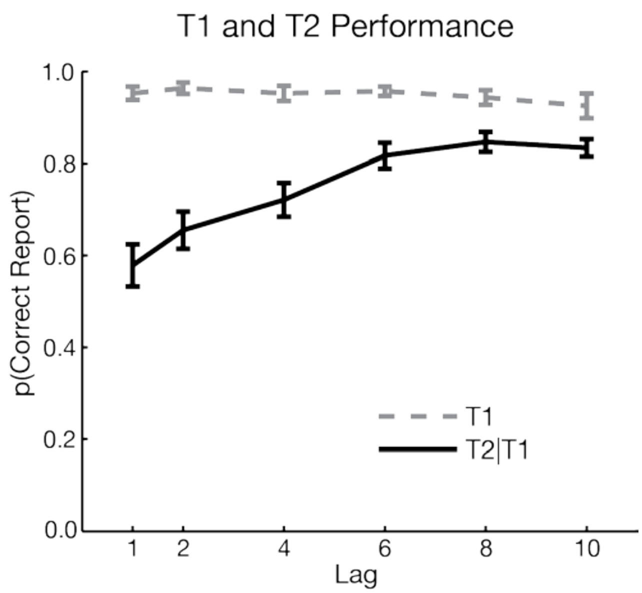
*Analysis*

T1 and T2 performance was determined as percent correct at each lag. T2 performance was calculated using only trials where T1 was correct (T2|T1). One-way, within-subjects ANOVAs determined whether lag affected target performance.

DOI:10.1177/0956797613513810

**Results**

Lag had no effect on T1 performance ($F_{5,50} = 1.41$, $p = 0.24$). Importantly, T2 performance increased with lag ($F_{5,50} = 18.14$, $p < 0.001$), indicating that this color RSVP design produces an attention blink (Supplementary Fig. 1), consistent with other AB studies (e.g. Ross & Jolicoeur, 1999).




**Supplementary Figure 1**. Results of the standard color AB paradigm. Target detection (probability of correct report) as a function of the lag between T1 and T2. T2 performance was calculated using trials with correct T1 report (T2|T1). Error bars reflect standard error of the mean (SEM).

**Supplementary Experiment 2: Color AB with reduced frame rate (mixture modeling)**

For Experiment 1 (Color AB task) in the main text, we observed low $P_e$ for T2 (50-70%). Consequently, we considered the possibility that T2 perception was too impoverished to observe effects on precision. In this follow-up experiment, we increased T2 performance by reducing the RSVP rate, testing whether precision effects could still be observed with high $P_e$.

**Methods**

*Participants*

Eleven subjects (5 males, 18-30 years old) from the Vanderbilt Community participated in the experiment.

*Stimuli, procedure, and analysis*

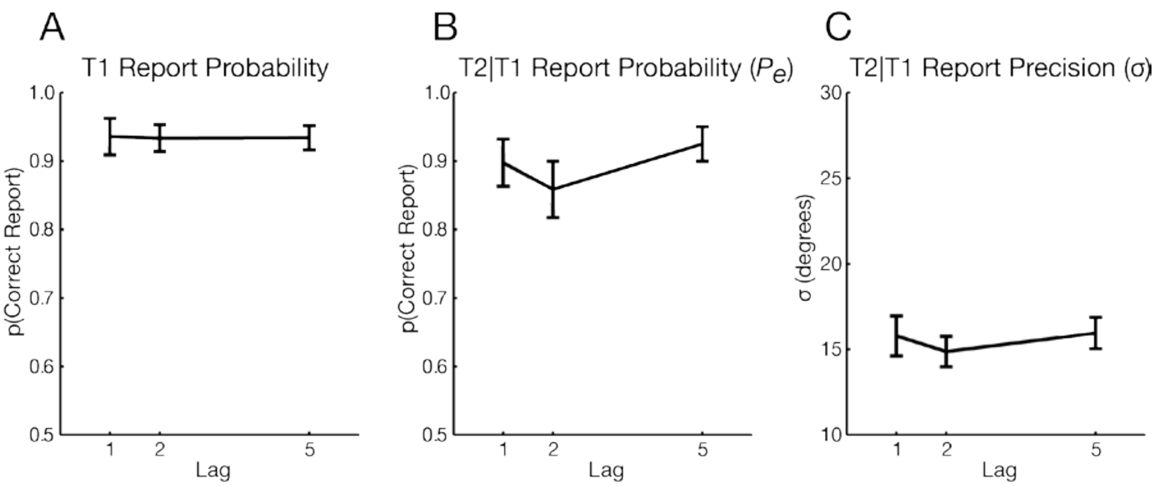
The experiment was identical to Experiment 1 (Color AB Task) except that target encoding was made less difficult by increasing the average frame duration from 115 ± 10 ms to 254 ± 46 ms. Specifically, beginning at 200 ms, the frame duration was adjusted

DOI:10.1177/0956797613513810

(+/- <= 30 ms) every 30 trials so that the percentage of T2 responses with less than 45 degrees of error remained around 90% for lags 1 and 2. In addition, we tested lag 5 instead of lags 4 and 8, as T2 at lag 5 was already well outside the blink window.

**Results**

Although T2 encoding probability ($P_e$) was much higher (between 80% and 95%) than in Experiment 1, there was still an effect of lag on $P_e$ ($F_{2,20} = 4.51$, $p = 0.02$; Supplementary Fig. 2), with worse performance at lag 2 than lag 5. In contrast, there was no effect of lag on precision (σ) estimates ($F_{2,20} = 1.04$, $p = 0.37$). Thus, target precision is unaffected in the AB with color stimuli, regardless of encoding opportunity.




**Supplementary Figure 2**. Results of the color AB task with reduced frame rate (Supplementary Experiment 2). A) T1 results showing no effect of lag. B) Probability ($P_e$) of T2 encoding. C) Precision (σ) of T2 encoding, where lower σ values (standard deviation of report error) correspond to better precision. Error bars reflect standard error of the mean (SEM).

**Supplementary Experiment 3: Standard face AB**

The purpose of this experiment was to verify that the face AB task used in the mixture modeling experiment of the Main text yielded a standard AB when the T2 probe was discrete, as is typical for an AB task.

**Methods**

*Participants*

Nine subjects (4 males, 18-26 years old) from the Vanderbilt Community participated in this experiment.

*Stimuli and Procedure*

Each trial consisted of the rapid serial presentation of two masked face targets for subsequent report. T1 was one of two female faces (4.2 x 4.2º). The T2 target and mask stimuli consisted of morphed grayscale faces and mosaic scrambles of these faces, respectively. The T2 probe face (4.2 x 4.2º) could be one of six possible faces created from a set of three distinct male faces and the morph between each pair. Scrambled faces (6.3 x 6.3º) were created in Matlab by dividing a given morphed face into 16 tiles, which were scrambled and then used to tile a 6x6 grid with replacement.

The experimental procedure closely followed the diagram in Fig. 4 of the main text. A trial began with the presentation of a fixation dot (500 ms), followed by T1 (150 ms), and then a scrambled face that served as a backwards mask (100 ms). Three different T1-T2 stimulus onset asynchronies (SOAs) were employed. The Long (850 ms) and Medium (550 ms) SOA conditions had scrambled faces (100 ms) preceding and following T2. In the Short SOA condition (250 ms), T2 and its mask immediately followed T1's mask. These sequences ensured that T2 was equally masked across conditions, as the T1 backward mask in the Short SOA condition also served as forward mask for T2. In addition to the SOA manipulation, the duration of T2 was also manipulated (100 ms for Short Duration or 200 ms for Long Duration), thus creating a 2x3 design. To prevent subjects from focusing exclusively on specific locations on each face, each stimulus' position was jittered by up to 0.7º.

A T2 probe followed 210 ms after T2 mask presentation; this probe consisted of one of the 6 possible T2 faces. Subjects pressed one of two keys to report whether the probe face was the same as or different from T2 (50% probability). After the T2 response, a display asking 'First Face?' prompted subjects to indicate by button press which of the two female faces had been presented as T1. The next trial began after a 200 ms blank screen.

Each subject undertook 8 practice trials before completing 36 blocks of 30 trials each. For the first 17 blocks, subjects were not instructed about, and did not perform, the T1 task (Ignore-T1 condition), although the T1 stimuli and masks were still shown. For the remaining blocks, participants were instructed to pay attention to and perform the T1 task (Report-T1 condition). This manipulation was employed to test whether T2 performance was affected by top-down attentional allocation to T1, as this is a key characteristic of the AB (Raymond et al., 1992; Nieuweistein et al., 2009).

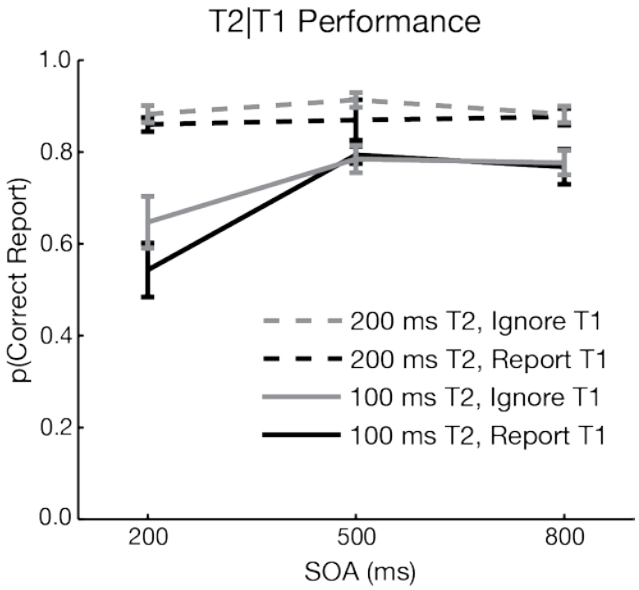
**Results**

There were effects of both SOA ($F_{2,16} = 38.51$, $p < 0.001$) and T2 duration ($F_{1,8} = 47.19$, $p < 0.001$) on T2 performance in the Report-T1 condition, with better T2 performance at longer SOAs and T2 durations (Supplementary Fig. 3; SOA x T2 duration interaction: $F_{2,16} = 4.69$, $p = 0.03$). Similar main effects of SOA and T2 duration on T2 performance were present in the Ignore-T1 condition ($F_{2,16} = 6.3$, $p = 0.01$ and $F_{1,8} = 40.94$, $p < 0.001$), though the interaction between factors was not significant ($p = 0.23$).

The results of the Ignore-T1 condition suggest that presentation of a T1 face, even when task-irrelevant, is sufficient to capture some attention and thus impair detection of a subsequently-presented, task-relevant face. That the T1 face attracted attention is not surprising because it was the first stimulus shown in the trial and belonged to the same stimulus category as the task-relevant T2 face (Folk et al., 1992). Importantly, the transient T2 deficit for the 100 ms T2 duration – the duration at which an AB is typically observed – was larger when T1 was task-relevant than when it was not (SOA x T1 Report; $F_{2,16} = 10.65$, $p = 0.001$). These results indicate that attending to and processing

DOI:10.1177/0956797613513810

T1 in a goal-directed fashion significantly increases the T2 deficit in the Report-T1 condition.




**Supplementary Figure 3**. T2 performance (probability of correct report) in a standard face AB task. Strong ABs are observed for short (100 ms, solid lines) but not long (200 ms, dashed lines) T2 durations. The AB is also stronger in the Report-T1 condition (black lines) than in the Ignore-T1 condition (gray lines). Error bars reflect SEM.

**Supplementary Experiment 4: Ignore-T1 face AB experiment (mixture modeling)**

In a mixture modeling experiment, we tested whether T2 performance depended on attention to and perception of T1, a key characteristic of the AB (Raymond et al., 1992; Nieuweistein et al., 2009). To do so, we had a separate group of subjects perform an Ignore-T1 version of Experiment 2 of the main text.

**Methods**

*Participants*

Sixteen young adults (4 males, age range 18-29) participated. The data from three additional participants were excluded because their T2 accuracy was too low ($P_e$ < 10%) to obtain reliable σ estimates.

*Stimuli and Procedure*

The methods were the same as in the Report-T1 experiment (Experiment 2, main text) except that participants were instructed to ignore T1, and the T1 probe response display was not shown. As no T1 data were collected, T2 was not analyzed conditional on T1 performance.

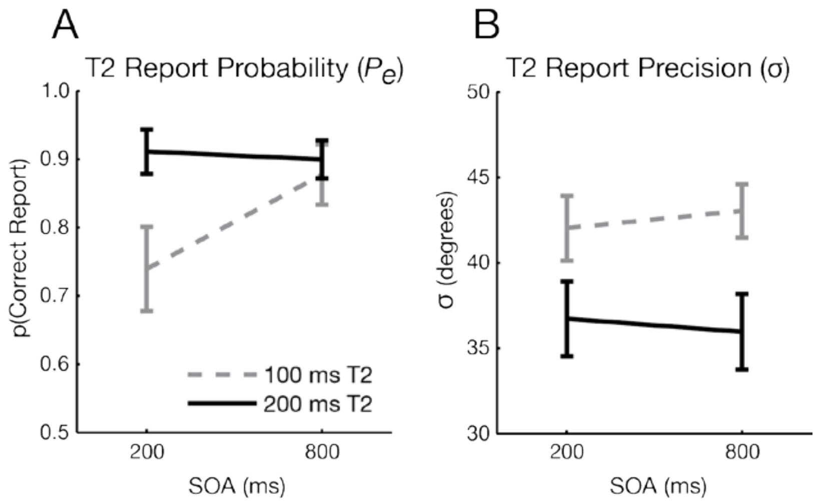
**Results**

$P_e$ was lowest when both the SOA and T2 duration were short (Supplementary Fig. 4A; interaction of SOA x T2 duration: $F_{1,15}$ = 8.40, $p$ = 0.01). Although there was

DOI:10.1177/0956797613513810

still evidence of T1 interfering with T2 report when participants ignored T1, the interference effect for the 100 ms T2 duration was smaller than when T1 was reported (Mixed-effects 2x2 ANOVA comparing the effects of SOA from the present experiment with Experiment 2 of the main text: $F_{1,30} = 5.08$, $p = 0.03$). The effects on precision were similar to those from the Report-T1 experiment: Precision was not affected by SOA ($F_{1,15}$=0.01, $p = 0.94$; Supplementary Fig. 4B), but it was improved with increased T2 duration ($F_{1,15} = 16.3$, $p = 0.001$).

These results indicate that attending to and processing T1 in a goal-directed fashion significantly contributes to the T2 deficit in the Report-T1 condition.




**Supplementary Figure 4.** Ignore-T1 face AB mixture modeling experiment. A) Probability ($P_e$) and B) precision (σ) of report for short (200 ms) and long (800 ms) SOAs. Faces were presented for either short (100 ms, gray dashed lines) or long (200 ms, solid black lines) durations. Error bars reflect SEM.

## Supplementary Experiment 5: Mixture modeling of seen/unseen T2

This experiment assessed whether the precision estimates derived from the mixture modeling analyses were based on consciously perceived and reported trials.

### Methods

*Participants*

Seven subjects (3 males, 20-24 years old) participated in this experiment.

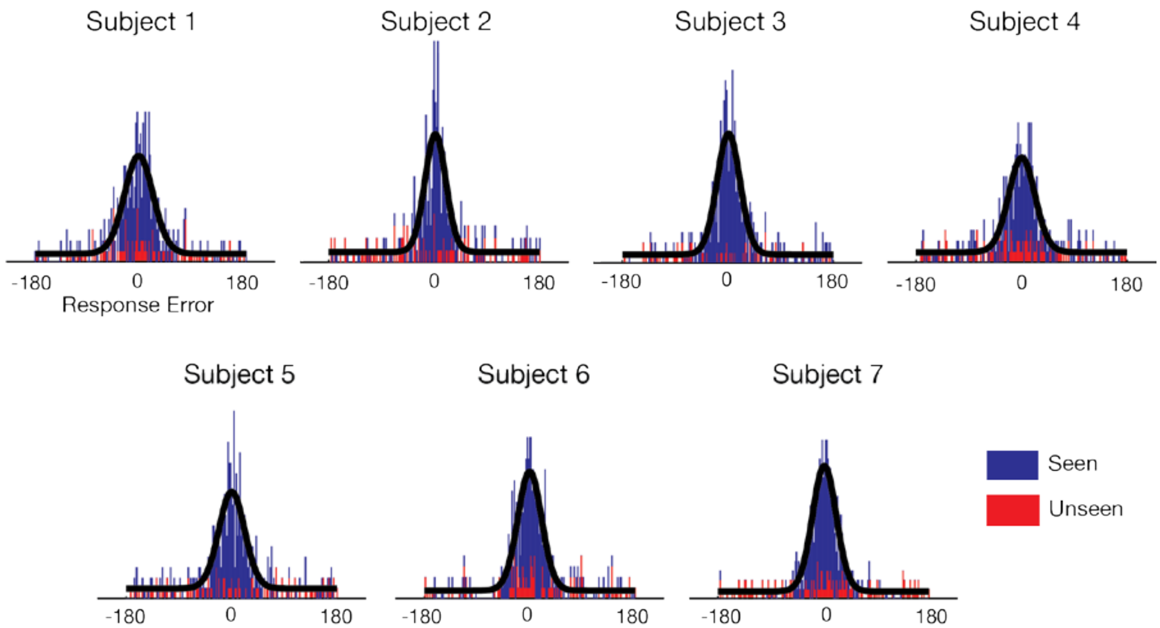
*Stimuli and Procedure*

The experimental paradigm was the same as Experiment 1 of the main text with the following adjustments. First, T2 was always presented at lag 4. Second, the frame rate was held constant at 115 ms per item throughout the experiment. Third, each experimental session included between 5 and 8 blocks, each containing 64 trials. Finally, after indicating T2's color on a color wheel, subjects reported whether they had seen or not seen the target.

DOI:10.1177/0956797613513810

**Results**

As is evident in the individual distributions (Supplementary Figure 5), the width of the mixture model fit (solid black line) is determined by the "seen" responses distribution, whereas the vast majority of "unseen" responses are random guesses. This result indicates that the precision estimates are derived from trials in which T2 is consciously perceived and reported.




**Supplementary Figure 5.** Individual response distributions for the seen/unseen T2 experiment (n=7). The black line indicates the best mixture model fit when seen and unseen trials were aggregated.

DOI:10.1177/0956797613513810

**Supplementary Analysis: Variable precision model**

Recently, two groups (Fougnie et al., 2012; van den Berg et al., 2012) have suggested that the precision with which items are encoded varies within and across trials. One version of this account argues that targets are always encoded (equivalent to $P_e = 1$), but with variable precision (van den Berg et al., 2012). Such a variable precision account could in principle describe the present data, with the flat areas of the error distributions corresponding to extremely low-quality (high $\sigma$) representations. We therefore examined whether a variable precision model ($\sigma$ and variance in $\sigma$) could explain the data as well as our original model ($P_e$ and $\sigma$), which assumes a mixture of random guesses and imprecise target reports.

Using the corrected Akaike Information Criterion (AICc) measure (see Suchow et al., 2013) and data from the blink condition (Lag 2 in Expt. 1 and short SOA & duration in Expt. 2), we found that the standard mixture model ($P_e$ and $\sigma$) provided a better fit for the vast majority of participants. This model fit better for 27 of 28 subjects (96%) in Expt. 1 and 14 of 16 subjects (88%) In Expt. 2.

To further investigate the different models, we fit each model to the error distributions from Expt. 1, Lag 2, aggregated across subjects. We then plotted the residuals of these fits (actual data minus simulated data based on the posterior of the model fit; Supplementary Fig. 6). Although the standard model fit the data well, the variable precision model did not, systematically underestimating the frequency of both small (e.g. 10 degrees) and large (e.g. 150 degrees) errors, while overestimating the frequency of errors around 40 degrees. Thus, the flat portions of the error distributions in our data appear to be better described as true guess states (trials without any T2 information) rather than extremely low-information trials, providing further evidence of discrete perception in the AB.

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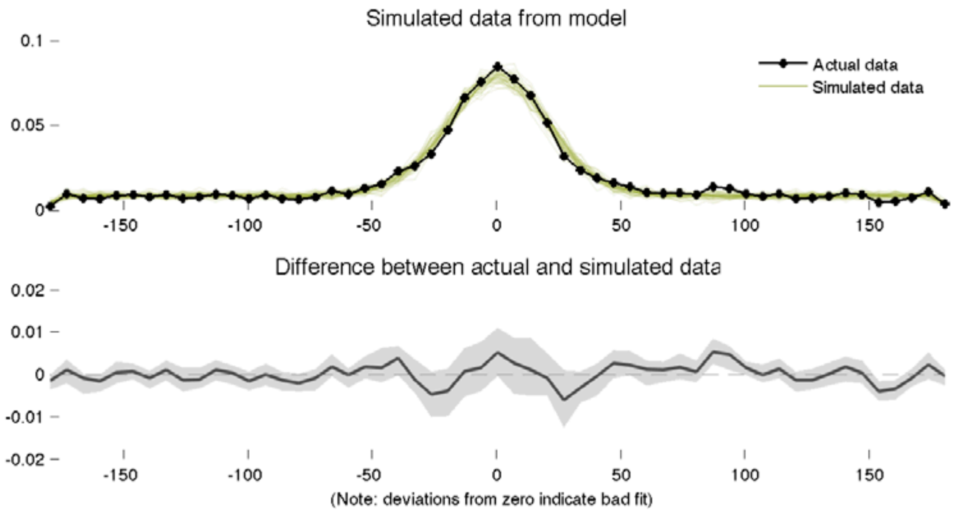
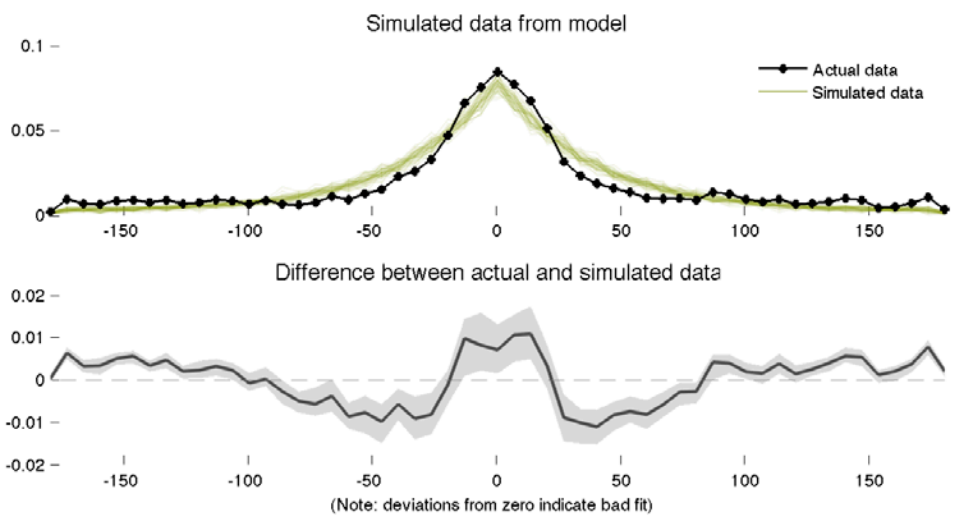
A. Standard model ($P_e$ and σ)




B. Variable precision model (σ and variance in σ)




**Supplementary Figure 6**. Simulated and actual T2 error distributions (aggregated across subjects) from Expt. 1, Lag 2. Top half of each panel: Data simulated from the indicated model fits (green) and the actual data (black). Bottom: The degree of mismatch between the simulated and real data, bounded by 95% confidence intervals. Where these intervals do not include zero, the model does not fit the data well. Plots were generated using the MemToolbox (Suchow et al., 2013).

DOI:10.1177/0956797613513810

**Supplementary References**

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception & Performance, 18*(4), 1030-44.

Fougnie, D., Suchow, J.W., & Alvarez, G.A. (2012). Variability in the quality of visual working memory. *Nature Communications, 3*, 1229.

Nieuwenstein, M., Van der Burg, E., Theeuwes, J., Wyble, B., & Potter, M. (2009). Temporal constraints on conscious vision: on the ubiquitous nature of the attentional blink. *Journal of Vision, 9*(9), 18, 1-14. doi: 10.1167/9.9.18

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: an attentional blink? *Journal of Experimental Psychology: Human Perception & Performance, 18*(3), 849-60.

Ross, N.E. & Jolicoeur, P. (1999). Attentional Blink for Color. *Journal of Experimental Psychology: Human Perception & Performance, 25*(6), 1483-94.

Rouder, J.N. & Morey, R.D. (2011). A Bayes-factor meta analysis of Bem's ESP claim. *Psychonomic Bulletin & Review, 18*, 682-689.

Rouder, J.N., Speckman, P.L., Sun, D., & Morey, R.D. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*(2), 225-237.

Suchow, J.W., Brady, T.F., Fougnie, D., & Alvarez, G.A. (2013). Modeling visual working memory with the MemToolbox. *Journal of Vision, 13*(10):9, 1-8.

van den Berg, R., Shin, H., Chou, W.C., George, R., & Ma, W.J. (2012). Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences USA, 109*(22): 8780-8785.

Zhang, W. & Luck, S.J. (2011). The number and quality of representations in working memory. *Psychological Science, 22*(11), 1434-1441.