

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

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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_c) 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 ($0.35^\circ \times 0.35^\circ$) that was followed by an RSVP stream of 10 to 23 colored disks and two square targets (T1 and T2;

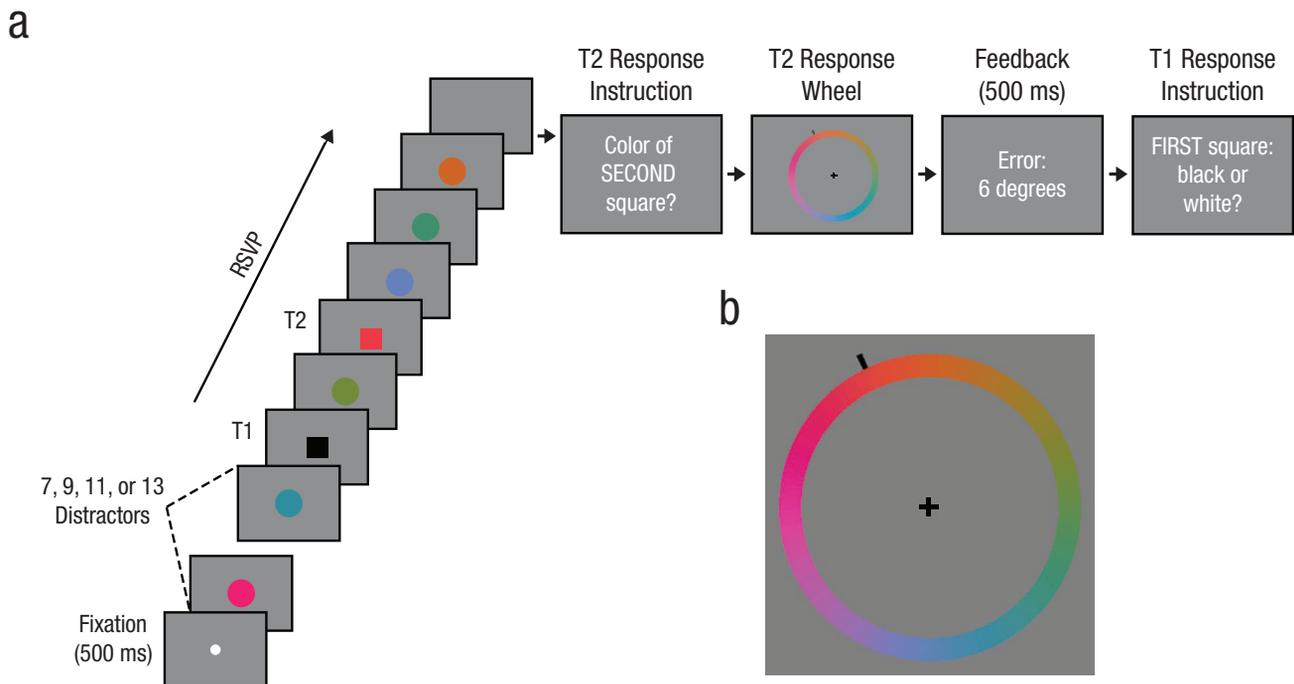


Fig. 1. The color attentional blink task (Experiment 1). Two targets (T1, T2) were embedded in a rapid serial visual presentation (RSVP) stream of colored circles (a). Subjects reported the color of T2 using a color wheel (b) and then reported whether T1 was black or white.

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 ($\pm \leq 20$ 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 (μ , a measure of bias) and concentration (k , a measure of spread, converted to σ ; 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 (μ) at Lag 1, no response bias was detected. Conventional parametric statistical tests were used to assess the effects of lag on σ 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

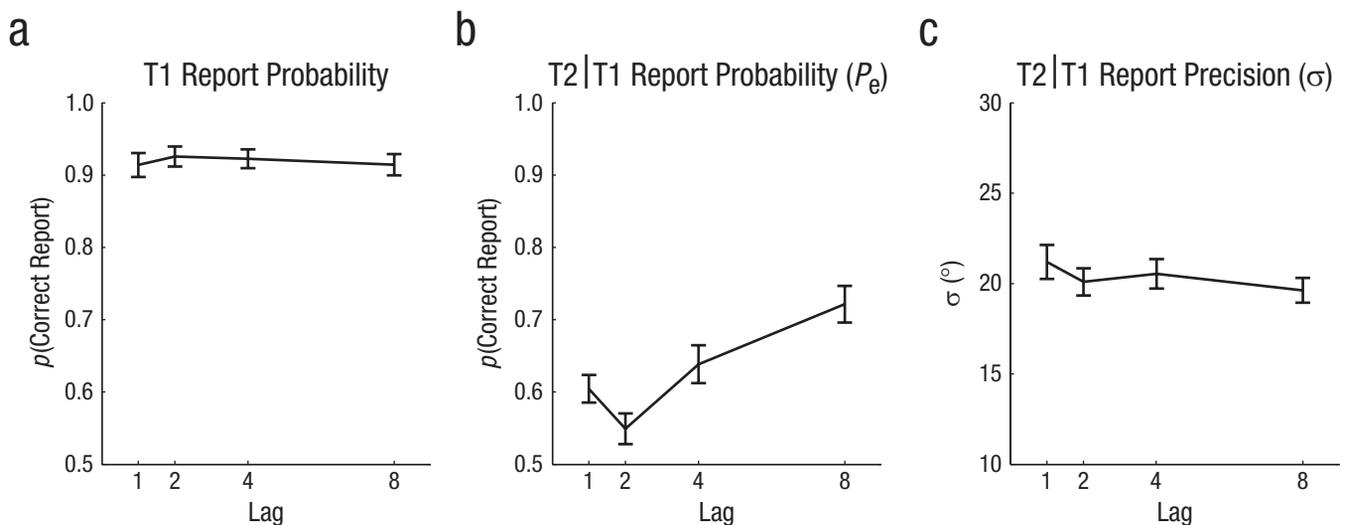


Fig. 2. Results for the color attentional blink task (Experiment 1): (a) probability of correct report of the first target (T1) as a function of the lag between T1 and the second target (T2), (b) probability of T2 encoding (P_e) as a function of T1-T2 lag, and (c) precision of T2 encoding (σ) as a function of T1-T2 lag. Note that lower σ 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.

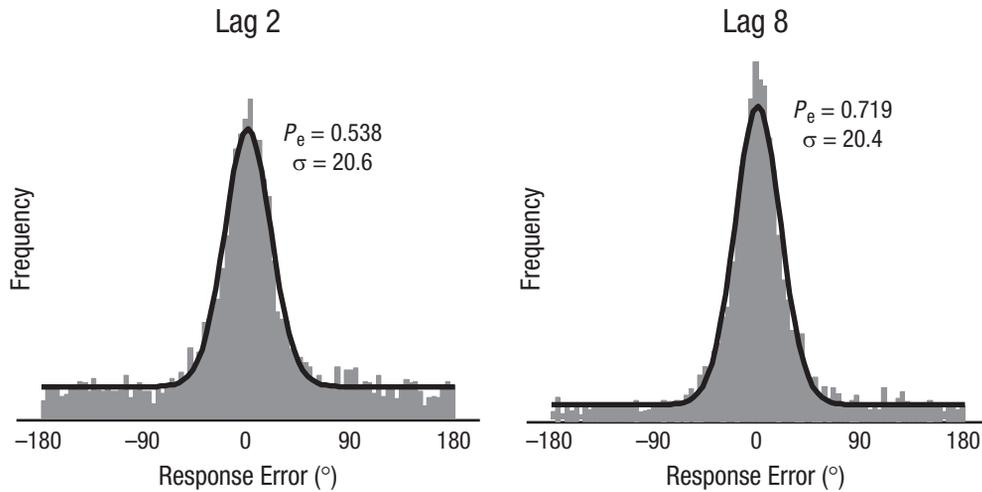


Fig. 3. Distribution of response errors for the second target (T2) in the color attentional blink task (Experiment 1), aggregated across all subjects separately for Lags 2 and 8. Each distribution was modeled (black line) as a mixture of two distributions, with nonguess responses drawn from a circular 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.

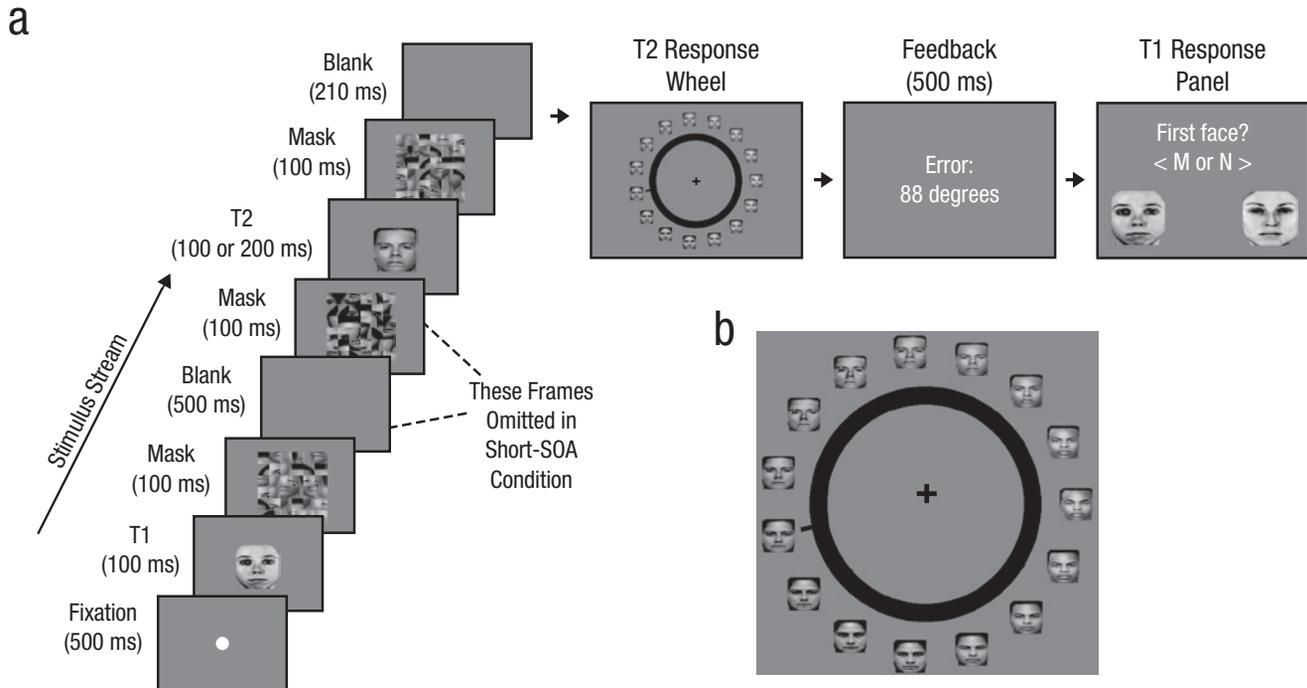


Fig. 4. The face attentional blink task (Experiment 2). As illustrated in (a), two masked faces (T1, the first target; T2, the second target) were presented sequentially with either a short (200 ms) or a long (800 ms) stimulus onset asynchrony (SOA). Subjects used a face wheel (b) to report the identity 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 $4.2^\circ \times 4.2^\circ$. The scrambled faces ($6.3^\circ \times 6.3^\circ$) 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 $2.0^\circ \times 2.0^\circ$ 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_c 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_c , the SOA \times T2 Duration interaction was significant, $F(1, 15) = 13.82, p = .002$. P_c 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

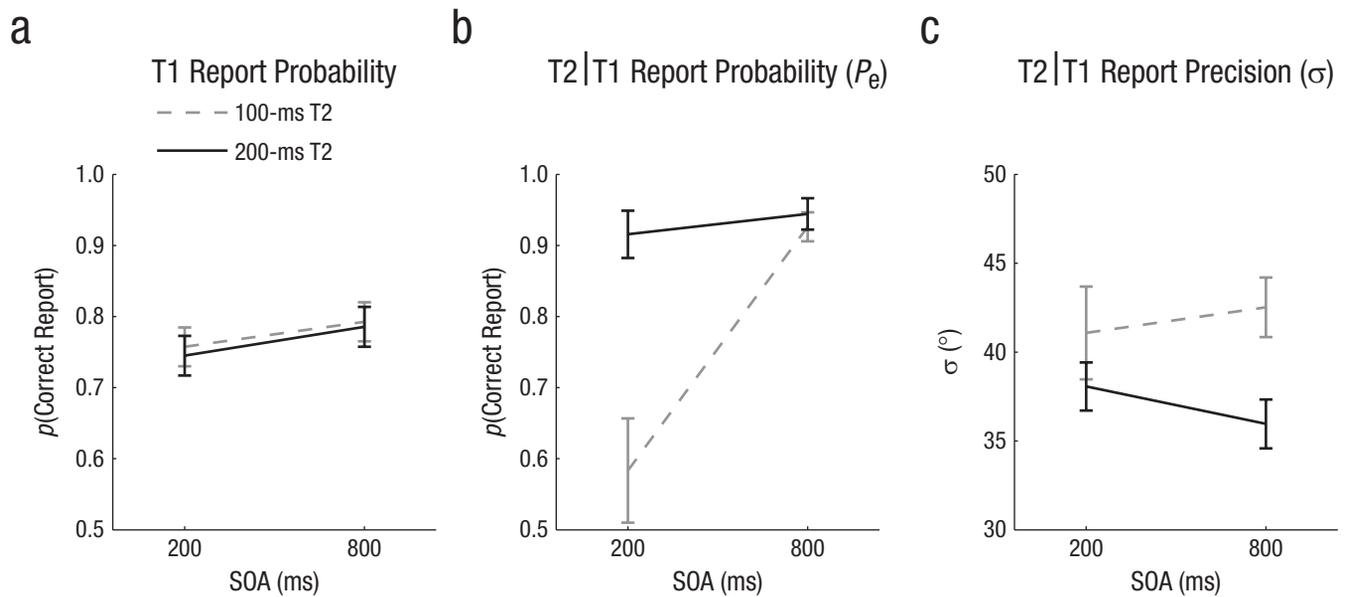


Fig. 5. Results for the face attentional blink task (Experiment 2): (a) probability of correct report of the first target (T1) as a function of stimulus onset asynchrony (SOA) between T1 and the second target (T2), (b) probability of T2 encoding (P_e) as a function of SOA, and (c) precision of T2 encoding (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 Fournie, 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. Fournie contributed to the study design. C. L. Asplund, D. Fournie, S. Zughni, and J. W. Martin collected data, and C. L. Asplund, D. Fournie, and S. Zughni analyzed data. R. Marois

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

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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.

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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.

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