1	
2	
3	Oculomotor freezing indicates conscious detection free of decision bias
4	
5	Alex L. White ^{1*} , James C. Moreland ² , and Martin Rolfs ³
6	
7	
8	
9	
10	
11	Running head: Oculomotor freezing is independent of decision bias
12	
13	
14	
15	
16	
17 18	
19	
20	
21	*Corresponding author, <u>alwhite@barnard.edu</u>
22	
23	¹ Department of Neuroscience & Behavior
24	Barnard College, Columbia University
25	76 Claremont Ave
26	New York, NY 10027, USA
27	
28 29	² Department of Psychology University of Washington
30	119 Guthrie Hall
31	Seattle, WA 98195, USA
32	
33	³ Department of Psychology
34	Humboldt-Universität zu Berlin,
35	Rudower Chaussee 18,
36	12489 Berlin, Germany
37	
38	
39 40	
40 41	
42	
43	
44	
45	
46	

47 Abstract

48 The appearance of a salient stimulus rapidly inhibits saccadic eye movements. Curiously, 49 this "oculomotor freezing" reflex is triggered only by stimuli that the observer reports seeing. 50 It remains unknown, however, if oculomotor freezing is linked to the observer's sensory 51 experience, or their decision that a stimulus was present. To dissociate between these 52 possibilities, we manipulated decision criterion via monetary payoffs and stimulus probability 53 in a detection task. These manipulations greatly shifted observers' decision criteria but did 54 not affect the degree to which microsaccades were inhibited by stimulus presence. 55 Moreover, the link between oculomotor freezing and explicit reports of stimulus presence 56 was stronger when the criterion was conservative rather than liberal. We conclude that the 57 sensory threshold for oculomotor freezing is independent of decision bias. Provided that 58 conscious experience is also unaffected by such bias, oculomotor freezing is an implicit 59 indicator of sensory awareness.

60 **Key words:** perceptual awareness; oculomotor freezing; microsaccades; perceptual 61 decision-making

62

63 New & Noteworthy

Sometimes a visual stimulus reaches awareness, and sometimes it does not. To understand why, we need objective, bias-free measures of awareness. We discovered that a reflexive freezing of small eye movements indicates when an observer detects a stimulus. Furthermore, when we biased observers' decisions to report seeing the stimulus, the oculomotor reflex was unaltered. This suggests that the threshold for conscious perception is independent of the decision criterion and is revealed by oculomotor freezing.

70 Introduction

71 You can often gain insight into another person's mind by observing how they move their eyes 72 and what they choose to look at. But even when they attempt to keep their gaze still, tiny 73 involuntary eye movements reveal aspects of their mental state. Interspersed among slower 74 types of fixational eve movements, involuntary *microsaccades* rapidly shift the gaze direction 75 by small amounts (Rolfs 2009; Rucci and Poletti 2015). Microsaccades are in many ways 76 similar to large saccadic eye movements (Hafed 2011; Otero-Millan et al. 2013; Rolfs et al. 77 2008), and their frequency and timing are affected by other cognitive and motor processes. 78 For instance, microsaccade rates decrease in anticipation of sensory events(Abeles et al. 79 2020; Amit et al. 2019; Badde et al. 2020; Denison et al. 2019) and prior to voluntary eye and 80 hand movements (Betta and Turatto 2006; Rolfs et al. 2006).

81 A particularly striking oculomotor phenomenon is oculomotor freezing (White and Rolfs 82 2016): saccadic eye movements are momentarily and automatically inhibited by the 83 appearance of new stimuli(Engbert and Kliegl 2003; Hafed and Ignashchenkova 2013; 84 Reingold and Stampe 2002; Rolfs et al. 2008). Specifically, the onset of a stimulus – be it 85 auditory, tactile, or visual - causes a transient decrease in the spontaneous microsaccade 86 rate that lasts from roughly 100 to 400 ms, which is followed by a brief rebound above 87 baseline (Badde et al. 2020; Bonneh et al. 2015; Engbert and Kliegl 2003; Hafed and 88 Ignashchenkova 2013; Rolfs et al. 2008; Scholes et al. 2015).

89 We recently found that oculomotor freezing is triggered only by stimuli that the observer 90 detects (as measured by explicit report), revealing a possible link to visual awareness (White 91 and Rolfs 2016). In those experiments, we presented brief grating stimuli (Gabor patches) on 92 half the trials and asked the observers to report stimulus presence or absence. We 93 developed an algorithm to convert microsaccade rates into a measure of oculomotor 94 sensitivity (o) that can be compared to perceptual sensitivity (d). Contrast thresholds for the 95 two sensitivity measures were indistinguishable (consistent with contemporaneous work by 96 others (Bonneh et al. 2015; Scholes et al. 2015)). Crucially, the same physical stimulus gave 97 rise to full-fledged oculomotor freezing when it was detected but caused no change in 98 microsaccade rates when it was missed. Moreover, microsaccades were inhibited if 99 observers reported having seen a stimulus even if none had appeared. Because of this 100 correlation, a Bayesian algorithm could decode from observers' eye movement patterns

2

whether they had detected a stimulus or not. This oculomotor link to perception may provide
a new tool for studies of perception in incommunicative patients, children, or non-human
animals, and for "no-report" studies of consciousness (Tsuchiya et al. 2015).

104 The present study answers an important question left open by all previous studies: is 105 oculomotor freezing triggered by observers' sensory experience, or by their decision that a 106 stimulus was present? Those two phenomena can be dissociated, and understanding which 107 one lies at the origin of oculomotor freezing is vital to its interpretation and application. We 108 consider two hypotheses to explain the established covariation between oculomotor 109 responses and explicit perceptual detection (Bonneh et al. 2015; Denniss et al. 2018; 110 Scholes et al. 2015; White and Rolfs 2016). Both assume a classical signal detection model: 111 on each trial, the stimulus evokes an internal response that is compared against a criterion to 112 decide whether to produce a response or not. Even when the physical stimulus and task 113 demands are constant, the sensory response varies across trials, but the criterion is 114 relatively stable. The two hypotheses concern whether the criterion for oculomotor freezing is 115 the same as the criterion for explicit perceptual decisions.

(1) Shared criterion: There is a single decision criterion that determines both explicit
perceptual reports and oculomotor freezing. When the sensory response exceeds the
criterion, it triggers both a "yes" decision and oculomotor freezing. The shared criterion
can be strategically modified, to maximize expected rewards. In support of this possibility,
manipulations of stimulus probability that affect decision bias affect activity in the superior
colliculus (Crapse et al. 2018), which is also causally involved in controlling
microsaccades (Hafed et al. 2009).

123 (2) Distinct criteria: There are distinct criteria for triggering oculomotor freezing and for 124 deciding that a stimulus was present. However, while the oculomotor criterion is 125 inflexible, the observer can strategically change their perceptual decision criterion to 126 maximize expected rewards as conditions change. Thus, the two criteria can diverge, 127 breaking the link between explicit reports and oculomotor freezing. To explain our prior 128 results(White and Rolfs 2016), this hypothesis assumes that the participants reported 129 exactly what they perceived and set their decision criterion very near the criterion for 130 oculomotor freezing.

131 We designed two experiments to discriminate between these hypotheses by manipulating 132 observers' decision criterion in a detection task. The first experiment used weighted payoffs 133 (real money won or lost on each trial), and the second varied the expected probability that a 134 stimulus would appear on each trial. Such manipulations shift the theoretically optimal 135 criterion to a point that corresponds to a particular likelihood ratio β_{opt} of target presence to 136 absence, and have been shown to work empiricalally (Macmillan and Creelman 2005; Mulder 137 et al. 2012; Swets et al. 1961). Our question here is whether and how these bias 138 manipulations affect the prevalence of oculomotor freezing. To answer it, we conduct two 139 main analyses of microsaccade rates: the first separates trials according to the physical 140 stimulus presence, and the second additionally separates trials according to the participants' 141 reports of stimulus presence or absence. The shared-criteria hypotheses predict an effect of 142 bias condition in the first analysis but not the second, the distinct-criteria hypothesis predicts 143 the opposite.

144 METHODS

Both experiments were pre-registered (<u>https://osf.io/ycjgr</u>; <u>https://osf.io/s9myc/</u>). The Ethics Committee of the German Society for Psychology (DGPs) approved the study.

147 Experiment 1

Participants: We recruited a total of 16 observers from the Humboldt-Universität zu Berlin community, with normal or corrected-to-normal vision. They participated in exchange for a payment that depended on performance (details below). Of the 14 observers who completed the study (see below), 6 were male, 8 were female, and their ages ranged from 19 to 34 years (mean 26.3). All were naive as to the research aims, and gave informed consent.

The sample size was chosen on the basis of a power analysis based on the data from White & Rolfs (2016). In Experiment 3 of that study, we found an effect of orientation adaptation on microsaccade rates. That effect size was modest: the maximal difference at 350 ms poststimulus was 0.2 Hz. Averaging over the time window when the overall inhibitory effect of stimulus presence was significant, the mean effect was 0.13 Hz.

We made the conservative assumption that if there is an effect of payoff condition, it is 75% as large as the effect of orientation adaptation, at each individual timepoint. We conducted a

160 power analysis to determine how many participants would be necessary to find such an 161 effect with a power of 0.8. For each possible sample size (N) between 10 and 20, we 162 simulated 100 experiments. For each experiment, we conducted a bootstrapping analysis: in 163 each of 1000 repetition, we drew N observers with replacement from the original data set in 164 White & Rolfs (2016). For each observer, we computed the difference in microsaccade rate 165 between the unadapted and adapted condition, at each time point post-stimulus, multiplied 166 by 0.75. We then averaged those differences across the resampled participants. Over 1000 167 repetitions we built up a distribution of differences at each time-point, from which we could 168 extract a p-value. We applied the false discovery rate correction to determine at which time-169 points the difference was significant by applying. For each simulated experiment, we 170 considered the overall effect to be significant if the difference was significant in at least 10 171 individual time-points. For each N, we defined power as the proportion of experiments with a 172 significant effect. The minimal N to have a power over 0.8 was 14 (estimated power = 0.87).

173 Two participants began the study but did not finish it and were not included in the analyses.
174 One was unable to finish all the sessions, and another discontinued after three sessions with
175 d' far above the acceptable range, due to threshold estimation failure. Thus, the final sample
176 included 14 participants.

177 Apparatus and Stimuli

178 Observers sat in a darkened room with their head on a chin rest, 270 cm from a projection 179 screen that displayed stimuli with a gamma-linearized ProPixx projector (VPixx 180 Technologies; 120 Hz, 1920 x 1080 pixel resolution). We recorded the gaze position of both 181 eyes at 500 Hz with a head-mounted Eyelink 2 system (SR Research, Ontario, Canada). 182 Stimuli were controlled and data collected with the Psychophysics and Eyelink toolboxes 183 (Brainard 1997; Cornelissen et al. 2002; Pelli 1997). The grayscale display (1920 x 1080) 184 pixels, 120 Hz refresh rate) had 8 bits of resolution in luminance. The background luminance 185 was set to 35% of its maximum (18.15 cd/m²).

The fixation mark was a 4 by 4-pixel black-and-white checkerboard pattern of width 0.09 degrees of visual angle (dva). In between trials, this mark was replaced by a circle (0.27 dva radius) of alternating black and white pixels. The target stimulus was a Gabor pattern: a 0.75 cycles/dva, vertically oriented sinusoidal grating windowed by a two-dimensional Gaussian (σ = 0.67 dva).

191 Procedure

192 Observers began each trial by fixating on the central mark. After 0.5-2.5 s, the target Gabor 193 stimulus flashed for 8.3 ms. The target's onset time had a roughly flat hazard rate: on each 194 trial, the onset time was set to 0.5 s plus a value drawn from an exponential distribution 195 (Mean = 0.65 s) clipped at 2 s. The target's phase on each trial was randomly set to either 0° 196 or 180°. On 50% of the trials, the target had non-zero contrast (target-present trials). On the 197 remaining trials, its contrast was set to 0, causing no change on the screen (target-absent 198 trials). The fixation mark remained visible at the center of the Gabor. 492 ms after target 199 onset, a beep (400 Hz, 50 ms, delivered through headphones) indicated that the trial was 200 over.

The observer's task was to indicate whether the target was present or absent by pressing the up or down arrow, respectively, with the right hand. Response time was unlimited, but responses were not allowed before the beep. Tones delivered immediately after the response indicated whether the response was correct or incorrect, and how many points were won or lost (details in the next section). After an inter-trial interval (700 ms) containing only the circular fixation mark, the next trial began.

207 The first session began with practice and then two blocks of staircase trials to estimate the 208 observer's contrast threshold. During the staircase blocks, the contrast was adjusted after 209 each trial according to the single-interval adjustment matrix (SIAM) staircase procedure 210 (Kaernbach 1990). The contrast adjustment depended on the stimulus and response: after a 211 hit, -0.3 log₁₀ units; miss, +0.3 log₁₀ units; false alarm, +0.6 log₁₀ units; correct rejection, no 212 adjustment. The magnitudes of these steps were halved after the 1st and 2nd staircase 213 reversals. In each block, we interleaved two staircases, one starting at a relatively high and 214 the other at a low level of contrast. The block ended when both staircases underwent 10 215 additional reversals. The mean contrast of all but the first 2 reversal points provided the 216 threshold estimate. We defined the observer's contrast threshold as the mean of 4 threshold 217 estimates (2 from each of 2 blocks).

In the main experimental blocks (80 trials each), the target's contrast was set to the observer's estimated threshold. The mean stimulus contrast in included trials was 9% (ranging across individuals from 7% to 12%).

221 Payoff conditions

222 Our main manipulation is to the reward structure for correct and incorrect responses on 223 target-present and target-absent trials. On each trial the observer won or "points", which at 224 the end of the experiment were converted to a monetary payment (1600 points = \pounds 1). By 225 varying payoffs, we aimed to manipulate the observer's *detection criterion*: that is, how much 226 internal sensory evidence is required for the participant to report "target present" (Macmillan 227 and Creelman 2005; Swets et al. 1961). In the main experimental blocks, there were two 228 payoff conditions: conservative and liberal. Additionally, a neutral condition was used in the 229 initial staircase blocks to estimate contrast threshold. Following classic signal detection 230 theory, we assumed that on each trial the observer bases their decision on a single value r. 231 which is the amount of sensory evidence in favor of target presence. The probability 232 distribution of r on target-absent trials is $f_a(r)$, a Gaussian with $\mu=0$ and $\sigma=1$. The probability 233 distribution of r on target-present trials is $f_p(r)$, a Gaussian with $\mu = d'$ and $\sigma = 1$. d' is the 234 observer's sensitivity to the target. The observer's criterion can be expressed as c, the cutoff 235 value of r needed to report presence. A related measure is the observer's bias, the likelihood 236 ratio β :

$$\beta = \frac{f_p(c)}{f_a(c)}$$
(Eq. 1)

After substituting the full Gaussian formulas for f_p and f_a , we can reduce the equation to:

239 $\beta = e^{cd' - \frac{{d'}^2}{2}}$ (Eq. 2)

240 The payoffs in each condition were set to achieve a desired optimal criterion β_{opt} : the value of β that maximizes the expected reward. The values of β_{opt} were 3 for the conservative 241 242 condition, 1 for the neutral condition, and 1/3 for the liberal condition. We set the payoffs 243 such that the optimal observer, with a d' of 1.5, would earn an average of 6.4 points per trial. 244 Over 1280 trials, that would yield a payment of €5.12 at our exchange rate of 1600 points/€. 245 By setting the target luminance contrast to detection threshold, we aimed to keep each 246 observer's d' near 1.5. Given the average expected reward/trial (6.4 points) and the expected 247 d', we computed the payoff matrix that would lead an ideal observer to set their criterion to 248 the desired β_{opt} . Specifically, we computed the payoffs for target-present trials, R_p , and for 249 target-absent trials, R_a . For each trial type *j* (*j*=*p* for target-present; *j*=*a* for target-absent), the 250 reward for correct responses is R_i points and the reward for errors is $-R_i$ points.

On any given trial, there were four possible outcomes: hits or misses if a target was present, or correct rejections or false alarms if there was no target. Given *d'* and β , we can compute the probabilities of each of those outcomes. Given R_p and R_a , we can then compute the expected reward *V* per trial:

255
$$V = p(hit)R_p - p(miss)R_p + p(correct \ reject)R_a - p(false \ alarm)R_a$$
(Eq. 3)

Given that the prior probabilities of target presence and absence were both equal to 0.5, the optimal likelihood ratio criterion is the ratio of payoffs:

 $\beta_{opt} = \frac{R_a}{R_p}$ (Eq. 4)

Therefore, greater payoffs on target-absent trials should induce a conservative (higher) criterion, whereas greater payoffs on target-present trials should induce a liberal (lower) criterion. In our conservative condition ($\beta_{opt} = 3$), payoffs on target-absent trials should be three times payoffs on target-present trials. The inverse is true in the liberal condition. Working backwards from the equations above, and given our desired *d*' and expected reward per trial (*V*), we computed the payoff matrix shown in **Table 1**.

Table 1: Payoff matrix. For each condition, this table lists the number of points that can be won (positive values) or lost (negative values) for each type of response. The neutral condition was only used in the initial staircase blocks.

Condition	Hit (R_p)	Miss (-R _p)	Correct reject (R _a)	False alarm (-R _a)
Conservative	4.9	-4.9	14.8	-14.8
Liberal	14.8	-14.8	4.9	-4.9
Neutral	11.7	-11.7	11.7	-11.7

268

269 The payoff on each trial was indicated by a feedback tone immediately after the response. 270 These tones were composed of one, two, or three beeps, depending on the absolute value of 271 the payoff (as shown in **Table 1**, there were three possible magnitudes). When there were 272 multiple beeps, their pitches ascended in a major scale for correct responses or descended 273 in a minor scale for incorrect responses. Each beep was separated by 20 ms of silence. In 274 the liberal condition, for example, hits won 14.8 points and were followed by three ascending 275 beeps, whereas false alarms cost 4.9 points and were followed by one low-pitched beep. The 276 three beeps used for correct tones were: 75 ms of 440 Hz; 80 ms of 587 Hz; and 85 ms of 277 659 Hz. The three beeps used for incorrect feedback tones were: 75 ms of 196 Hz; 80 ms of 278 155 Hz; and 85 ms of 131 Hz.

279 The total number of points won were displayed at the end of each block. Prior to each block, 280 instructions regarding the payoff structure were displayed on the screen. These instructions 281 consisted of a 2x2 table showing the number of points that could be won or lost for reporting 282 "Yes" or "No" depending on whether a target was present or absent. The values in this table 283 were the same as in the corresponding condition's row in **Table 1**, rounded to the nearest 284 integer. A single sentence was written above the table: in the Conservative condition, 285 "Rewards and penalties are greatest when the target is absent."; in the Liberal condition, 286 "Rewards and penalties are greatest when the target is present."

287 Importantly, the words "liberal" or "conservative" were never said to the participants, nor did 288 experimenters tell them what the optimal strategy was for any given condition. However, in 289 the first training session, the participant read a longer document of instructions that said, "In 290 the main part of the experiment, we will vary the number of points you can win or lose 291 depending on presence of the target and the response you make. There are two types of 292 blocks that differ in the relative rewards and penalties on trials when the target was really 293 present or absent. To win the most money, you should adjust how sure you need to be to say 294 'yes' or 'no', depending on the points available for each type of response in the current 295 block." When introducing the conservative condition, the instructions said: "You will win three 296 times as many points when the target is absent and you say no, than when a target is 297 present and you say yes...and lose three times as many points when the target is absent 298 and you say yes, than when a target is present and you say no." Complementary instructions 299 followed for the liberal condition. Observers were also instructed that they could win points 300 and earn money during the staircase blocks as well as the main blocks.

In the first session, we informed observers that they would be paid a base hourly rate of $102 \ \epsilon^7$ /hour, plus a bonus equal to the total number of points they accumulated during the trials, divided by 1600. The maximum bonus they could earn in any given hour-long session was $104 \ \epsilon^4$. The mean bonus paid for two main experimental sessions was $104 \ \epsilon^4$. The mean bonus paid for two main experimental sessions was $104 \ \epsilon^4$.

Each participant completed a total of 8 blocks of each condition (for a total of 640 trials/condition). The first session began with practice, the staircase to estimate threshold, and if time permitted, some main experimental blocks. In each subsequent session (about one hour each), the typical observer completed 8 blocks: the first four of one payoff condition, and the next four of the other condition. In each session, observers thus did an

equal number of blocks of the two payoff conditions. The order of conditions alternated across sessions, and a random half of the observers started with the liberal condition.

313 Completing all 16 blocks required a total of three sessions for the typical participant 314 (including the first staircase session). At the start of the 2nd and 3rd sessions, a practice block 315 established whether the prior session's contrast threshold was still appropriate; in some 316 cases, it was necessary to re-evaluate the threshold and re-set the contrast level for that 317 session to keep d' near 1.5. If the overall d' in a full session (~8 blocks) was above 2.0 or 318 below 1.0, we excluded those blocks from analysis and re-ran them in an extra session. This 319 occurred when our threshold estimate was significantly inaccurate. A total of three sessions 320 from three participants were excluded and re-run in that fashion. The reason to exclude them 321 is that our analyses of interest depend on the target stimulus being at threshold visibility. 322 Importantly, we always excluded and re-ran the same number of blocks of each payoff 323 condition.

324 Eye-tracking

325 At the start of each block, we performed a 9-point calibration within a central square region, 326 21 dva wide. Every 28 trials, we performed a standard drift correction by having the observer 327 press a key while fixating a dot at the screen's center. If either eye's gaze position deviated 328 more than 2 dva from the fixation mark between the start of a trial start and the beep, that 329 trial was immediately terminated and repeated at the end of the block. We also detected 330 fixation breaks offline by defining, for each trial, the fixation position as the median gaze 331 coordinates during the first 100 ms of the trial, and fixation breaks as deviations >2 dva from 332 that. Trials with offline-detected fixation breaks were excluded from the analysis, but that only 333 excluded an average of 1 trial per participant (maximum 3).

334 Experiment 2

Participants: We recruited a total of 20 observers from the Humboldt-Universität zu Berlin community. All had normal or corrected-to-normal vision, participated in exchange for payment, and gave informed consent. Of the 14 observers who completed the study and were included in the analysis (see below), 4 were male, 10 were female, and their ages ranged from 20 to 37 years (mean 25.4).

We used the same number of participants as in Experiment 1, but with twice as many trials per condition. The reason is that this experiment contained a condition in which the target

was half as likely to appear (and we needed to separately analyze trials with and without targets). 6 participants were not included in the analysis because they discontinued participation before completing the study (in two cases because their d' was out of range in one or more completed sessions and they declined to repeat them). Thus, the final sample included 14 observers.

347 Procedure

348 All stimuli and methods in Experiment 2 were the same as in Experiment 1, except as noted 349 here. Observers began each trial by fixating on the central mark. Then a probability cue 350 appeared for 1 s. The target probability cues were formed of 12 dots (each 0.2 dva in 351 diameter) arranged in a ring around fixation (radius 3 dva). The dots on each trial were all of 352 the same color, either cyan or magenta. For half the observers, a cyan cue indicated low 353 target probability and magenta indicated high target probability. For the other half of 354 observers, the colors were reversed. Then, after a variable delay of 0.5-2.5 s, the target 355 Gabor stimulus flashed for 1 frame (8.3 ms), and the trial proceeded as in Experiment 1. The 356 mean stimulus contrast in included trials was 6% (ranging across individuals from 5% to 9%).

357 Feedback and rewards

The feedback and reward structures were matched to the "neutral" condition in Experiment 1 (used in the staircase blocks). The participants won 11.7 points on correct trials (hits or correct rejections) and lost 11.7 points on incorrect trials (misses or false alarms). The feedback tones were two ascending beeps or two descending beeps.

362 *Probability conditions*

Our main manipulation was the probability of a target being present on each trial (p_T). In "lowprobability" trials, $p_T = 0.25$, and on "high probability" trials, $p_T = 0.75$. Those trials were randomly intermixed, because if they were in separate blocks, there could be hysteresis effects due to different amounts of stimulation in each block. The cyan or magenta pre-cue indicated the target probability condition at the start of each trial.

Given the average expected reward/trial (6.4 points) and the expected d' (1.5), we computed the target probabilities that would lead an ideal observer to set their criterion to the desired β_{opt} . Using the expected reward on each trial (Eq. 3), we can compute β_{opt} from the ratio of payoffs, scaled by the ratio of the probability of no target and the probability of a target:

372
$$\beta_{opt} = \frac{R_a}{R_p} \frac{(1-p_T)}{p_t}$$
 (Eq. 5)

373 See Swets et al. (1961) for an equivalent derivation. In Experiment 2, $R_a = R_p = 11.7$ points. 374 Therefore,

$$\beta_{opt} = \frac{(1-p_T)}{p_T} \tag{Eq. 6}$$

In the low-probability condition, $p_T = 0.25$ and $\beta_{opt} = 3$, the same as in the conservative payoff condition of Experiment 1. In the high-probability condition, $p_T = 0.75$ and $\beta_{opt} = 1/3$, the same as in the liberal payoff condition of Experiment 1. We therefore label the low-probability condition as the conservative condition, and the high-probability condition as the liberal condition.

At the start of the experiment, the observer was instructed to pay attention to the colored probability cues and was told their exact meaning. We did not tell the observers *how* to use the cues, but we did tell them, "If you pay attention to the colored dots and adjust your responses accordingly, you could gain roughly 20% more money than if you ignore them!". Prior to each block, we displayed a reminder about what the probability cues mean.

Each participant completed a total of 32 blocks of the experiment (80 blocks per trial, for a
total of 2560 trials, 1280 per condition). Completing all 32 blocks required a total of five or 6
sessions for the typical participant (including the first staircase session). The mean bonus
paid for the main experimental sessions was €10.67 (range €7.61 to €13.64).

As in Experiment 1, we excluded and re-ran sessions with d' above 2.0 or below 1.0. That occurred for a total of 5 sessions, one per each of 5 observers. On average, less than 0.1% of trials were excluded for offline fixation breaks (max 0.3%).

393 Analyses

394 Perceptual data analysis

We excluded trials with reaction times >4 SDs above the observer's median. Across participants, this criterion excluded an average of 1% of trials in Experiment 1 (maximum 1.6%), and an average of 0.7% in Experiment 2 (maximum 1.4%). We then computed perceptual sensitivity in each condition using the observer's hit rate (HR, the proportion of 'yes' responses on target-present trials) and false alarm rate (FR, the proportion of 'yes' responses on target-absent trials):

$$d' = z(HR) - z(FR)$$
(Eq. 7)

402 where *z* is the inverse of the normal cumulative distribution function. To avoid undefined *d'* 403 values, HR and FR were not allowed to fall below 1/(2N) nor to exceed (1-1/(2N)), where N 404 is the number of target-present or absent trials. For example, if the hit rate was 1, we 405 assumed that, had we run twice as many trials, there would have been 1 miss. We also 406 report the observer's criterion

$$c = z(1-FR) \tag{Eq. 8}$$

408 From that, we compute the bias β , the likelihood ratio, using Equation 2 defined above.

409 To evaluate the effect of payoff condition on these perceptual measures (d' and β), we used 410 bootstrapping to estimate 95% confidence intervals between pairs of conditions. A difference 411 is deemed significant if the 95% confidence interval excludes 0 (a two-tailed test).

412 Microsaccade detection

413 The trial exclusion criteria applied in the perceptual data analysis (see above) also applied to 414 the eye movement analysis. Our analysis of eye movement traces followed the procedure 415 reported in our previous paper (White and Rolfs 2016). We first transformed the raw gaze 416 positions into velocities (dva/s) and smoothed them by averaging over neighboring pairs of 417 two samples. Then, we identified microsaccadic events as shifts in gaze position with 2D 418 velocities that exceed-for at least 3 samples-an ellipse with horizontal and vertical radii 419 equal to five times the horizontal and vertical median-based standard deviations, respectively 420 (Engbert and Mergenthaler 2006). However, for 6 observers in Experiment 1, and 3 in 421 Experiment 2, the fixed threshold of 5 SDs yields very few microsaccades, so we lowered the 422 threshold to 4.

423 Monocular microsaccadic events less than 10 ms apart were merged. We defined binocular 424 microsaccades as those with at least 1 sample of overlap between the two eyes, and again, 425 merged binocular microsaccades less than 10 ms apart. We defined microsaccade onset as 426 the time the first of the two eye velocities exceeded the threshold, and offset as the timepoint 427 just before the last eye's velocity dropped below threshold. Other parameters (e.g., 428 amplitude) were averaged over the two eyes. We included in the analysis only binocular 429 microsaccades with durations \ge 6 ms, amplitudes \le 1 dva, and peak velocities \le 250 dva/s.

430 Microsaccade rate analysis

We then determined the time-varying microsaccade rate for each experimental condition with a smoothing procedure. First, we counted the number of microsaccades detected at each millisecond t relative to target onset, across all trials in each condition. Then, for each time point t, we computed a weighted sum of microsaccades in the local interval, using a "causal" kernel:

436

$$\omega(\tau) = \alpha^2 \tau e^{-\alpha \tau}$$
 (Eq. 9)

437 ω describes the weight given to microsaccades τ ms before time point t. We shifted the filter 438 by 1/ α ms to avoid a temporal bias and give the most weight to microsaccades at point t 439 (Rolfs et al. 2008; Widmann et al. 2014). The parameter α was set to 1/25. The smoothed 440 rate r(t) is the weighted sum of microsaccades divided by the total number of trials in the 441 sample, and converted into Hz by multiplying by 1000. Microsaccade rates were computed 442 from -350 to +500 ms relative to target onset.

443 To estimate the statistical significance of changes in microsaccade rates, we bootstrapped 444 them by simulating 1000 repetitions of the experiment (Efron and Tibshirani 1993). On each 445 repetition, we resampled with replacement from the set of observers then took the mean 446 between conditions. That gave us distributions of differences at each time point. The two-447 tailed bootstrapped p-value is defined as twice the proportion of differences that fell below 0. 448 When evaluating differences at many time points, we applied the false discovery rate 449 correction (Benjamini and Hochberg 1995). Two conditions are deemed significantly different 450 if the 95% confidence interval of differences does not include zero (corrected p<0.05). (Note: 451 this bootstrapping procedure differs from what we pre-registered, in that it is simpler and 452 focuses on variability across observers rather than variability across trials within each 453 observer, thus being a nonparametric analogue of a t-test).

To directly compare changes in microsaccade rate to perceptual sensitivity, we computed an analogous estimate of oculomotor sensitivity (White and Rolfs 2016). At each millisecond, the lack of a microsaccade following a stimulus is a "hit", and the lack of a microsaccade following no stimulus is a "false alarm". From the resulting oculomotor hit rate (HR) and false alarm rates (FAR), we can compute oculomotor d'_o at each time point t relative to stimulus onset (0<=t<=500):

460
$$d'_{o}(t) = z(HR(t)) - z(FAR(t))$$
 (Eq. 10)

14

461 Like perceptual d', this measure requires correction if HR or FAR reach extreme values. This 462 can happen if no microsaccade were detected during a period around t as wide as the base 463 B of the filter (~200 ms). Therefore, both rates will not be allowed to fall below 1/(2NB) nor to 464 exceed (1-1/(2NB)), where N is the number of target-present or absent trials, respectively. 465 That is, we assume that had we run twice as many trials, we would have found at least 1 466 microsaccade (a 'miss') in the 200 ms time-window surrounding any given time point. 467 Nonetheless, because microsaccades occur only about once or twice every second, both HR 468 and FAR at individual (millisecond) time points will be high (above 0.999). But because HR 469 rose even higher than FAR after stimulus presentation, we found positive values of d'_{o} .

To extract a single oculomotor sensitivity measure from an entire rate time course for a given condition, we defined a value o'; the maximum of the cumulative sum of d'_o values across time (within 200 to 550 ms post-stimulus). o' is unaffected by rate rebounds following inhibition, which result in negative d'_o . Pairwise differences in o' (across payoff conditions) were tested with bootstrapping, similar to perceptual d' as described above.

475 In addition to the pre-registered analyses reported thus far, we conducted two exploratory 476 analyses. First, to simplify the comparison of microsaccade rates across conditions (without 477 relying on hundreds of noisy tests at many individual time points), we computed the 478 microsaccade rates integrated across two time windows: for the baseline microsaccade rate 479 on target absent trials, we used the time window 0 to 500 ms. For target present trials, we 480 used the time window within which the microsaccade rate on target present trials was 481 significantly lower than the rate on target absent trials, for both bias conditions (bootstrapped 482 FDR-corrected p<0.05). This is the time window of significant oculomotor freezing (see 483 results).

484 Second, compared to our previous studies, we found that baseline microsaccade rates were 485 lower on average and more variable across, which complicates comparing rates by taking 486 simple differences (liberal-conservative) between conditions. We therefore computed 487 modulation indices that are more robust to variation across observers in overall 488 microsaccade rates: (A - B) / (A + B), where A and B refer to a measure in specific 489 conditions (e.g., microsaccade rate on conservative vs liberal trials; or report-present vs 490 report-absent trials). This index ranges from -1 to 1, where positive values indicate higher 491 microsaccades rates in A as compared to B, and negative values indicate the opposite.

15

492 Finally, we supplement our pairwise tests with Bayes Factors (BFs), which quantify strength 493 of evidence. In this context, a BF is the ratio of the probability of the data under the alternate 494 hypothesis (that two conditions differ), relative to the probability of the data under the null 495 hypothesis (that there is no difference) (Rouder et al. 2009, 2012). As an example, a BF of 496 10 indicates that the data are ten times more likely under the alternate hypothesis than the 497 null hypothesis. Typically, BFs between 1 and 3 are regarded as weak evidence for the 498 alternate hypothesis, BFs between 3 and 10 as substantial evidence, and BFs between 10 499 and 100 as strong evidence (Kass and Raftery 1995). Conversely, BFs between than 1/3 and 500 1/10 are considered substantial evidence for the null hypothesis, etc. We computed BFs for 501 pairwise t-tests and two-way repeated measures ANOVAs using the bayesFactor toolbox by 502 Bart Krekelberg (https://github.com/klabhub/bayesFactor: DOI: 10.5281/zenodo.4394422).

503

504 **RESULTS**

505 Explicit perceptual reports: Bias manipulations affect decision criteria but not sensitivity

506 On each trial, observers reported the presence or absence of a brief Gabor stimulus with a 507 luminance contrast that had been set to their individual detection threshold. The time of the 508 target's onset was unpredictable, but the end of each trial was indicated by a beep 500 ms 509 after the time of (potential) target appearance. The observers' goal was to win "points" that 510 were converted to bonus monetary payments. Correct responses (hits and correct rejections) 511 gained points and incorrect responses (misses and false alarms) lost points.

512 In Experiment 1, we introduced asymmetric monetary payoffs to manipulate decision bias. In 513 the liberal condition, rewards were three times greater for hits than correct rejections, and 514 penalties were three times greater for misses than false alarms. This reward structure places 515 the optimal criterion at the level of sensory evidence that is three times as likely to be 516 observed when the target is absent than present. Thus, the optimal likelihood ratio $\beta_{out} = 1/3$. 517 In the conservative condition, rewards were three times greater for correct rejections than 518 hits, and penalties were three times greater for false alarms than misses. That makes β_{opt} = 519 3. The reward structure varied across blocks of trials and was known to the participant in 520 advance. Feedback at the end of each trial indicated the reward magnitude.

521 In Experiment 2, we manipulated probability that a target would appear, and informed 522 observers of that probability on each trial. In the liberal condition, there was a 75% chance that a target would appear (3x likelier to be present than absent), which lowered the optimal criterion such that $\beta_{opt} = 1/3$. In the conservative condition, there was a 25% chance that a target would appear, raising the optimal criterion such that $\beta_{opt} = 3$ (as in Experiment 1). These trial types were randomly intermingled within blocks, but a cue in the form of colored dots presented at the start of each trial informed the participant of the target probability. Payoffs on target-presence and target-absent trials were of equal magnitude.

529 In both experiments, the bias manipulation strongly affected explicit perceptual reports of

- 530 target presence. The mean hit and false alarm rates, their mean differences between bias
- 531 conditions, and the 95% confidence interval (CI) of those differences, are listed in **Table 2**.

532 Hit rates and false alarm rates were much lower in the conservative than liberal condition,

533 indicating that participants were less willing to report seeing a target when the potential

534 payoffs were greater on target absent trials (Experiment 1), and when target presence was

535 unlikely (Experiment 2). Response times are plotted in **Supplementary Figure 1**

536 (https://osf.io/t9by7/).

		Conservative	Liberal	Diff	Diff 95% CI	
Hit rate	Expt 1	0.57 (0.02)	0.79 (0.01)	0.22 (0.03)	[0.18 0.27]	
	Expt 2	0.41 (0.02)	0.73 (0.04)	0.32 (0.05)	[0.22 0.40]	
False alarm rate	Expt 1	0.06 (0.01)	0.38 (0.04)	0.31 (0.04)	[0.24 0.40]	
	Expt 2	0.07 (0.01)	0.45 (0.07)	0.38 (0.07)	[0.27 0.52]	
d'	Expt 1	1.95 (0.12)	1.90 (0.10)	-0.05 (0.08)	[-0.22 0.09]	
	Expt 2	1.12 (0.09)	1.27 (0.07)	0.15 (0.11)	[-0.02 0.40]	
β Εχρ		2.32 (0.38)	0.42 (0.02)	-1.89 (0.39)	[-2.72 -1.29]	
	Expt 2	1.80 (0.09)	0.59 (0.06)	-1.21 (0.11)	[-1.39 -0.99]	

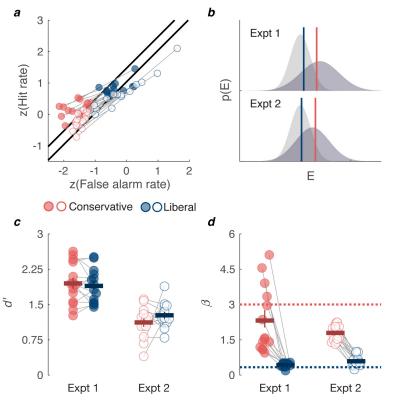
Table 2: Explicit reports in each condition of each experiment. The first two columns list the across-subject mean values, with the standard error in parentheses. The column labeled "Diff" is the average (and SEM) difference: liberal – conservative. The final column is the 95% bootstrapped confidence interval (CI) of the difference. When a CI excludes 0, we conclude there is a significant effect of the bias condition. *d' and* β are sensitivity and bias measures assuming unequal variance of sensory evidence on target-present and target-absent trials (see text).

To interpret these psychophysical data, we adopt the classic signal detection model: the participant reports target presence if the magnitude of sensory evidence E exceeds a criterion level c. The variances of E on target-absent and target-present trials are often unequal, and can be estimated with a receiver operating characteristic (ROC) graph (Swets

547 et al. 1961). The ROC in **Figure 1a** plots false alarm rates vs hit rates, each z-transformed 548 through the inverse normal cumulative distribution function. For each participant, one line 549 connects their points for the liberal (blue) and conservative (red) conditions. If the 550 distributions of sensory evidence have equal variance, then these lines should have slopes 551 equal to 1 (illustrated with thick diagonal black lines). The empirical slopes are consistently 552 shallower: in Experiment 1, the mean slope was 0.53 (95% CI = [0.46 0.60]), and in 553 Experiment 2 it was 0.60 (95% CI = [0.50 0.69]). Assuming that the target-absent 554 distributions have standard deviations (SDs) equal to 1, the SD of the target-present 555 distributions are equal to the inverse of the ROC slopes: 1.90 in Experiment 1 and 1.66 in 556 Experiment 2. These best-fitting signal detection models are shown in **Figure 1b**, with the 557 mean criteria (computed directly from false alarm rates) as vertical blue and red lines.

558 Using these estimated variances, we computed d', a measure of sensitivity (Figure 1c), and 559 β , a measure of bias (Figure 1d). d' is the distance between the mean E (sensory evidence) 560 on target-present trials and the mean E on target-absent trials. β is the likelihood ratio of target presence to target absence when E = c. Using the formulas for β and d' (Equations 2) 561 562 and 7) that typically assume equal variance, we substituted the best-fitting SDs into the 563 probability and cumulative density functions. Statistics for both measures are reported in 564 **Table 2.** d' did not significantly differ between the liberal and conservative conditions (CIs 565 include 0), but β was significantly higher in the conservative condition, for all participants. 566 The dashed lines in **Figure 1f** are the optimal β_{opt} in each condition. Most participants did not 567 shift their criteria guite far enough to reach the optimal levels (Kubovy 1977). For the 568 estimates of d' and β that (incorrectly) assume equal variance on present and absent trials, 569 see Supplementary Figure 2 (https://osf.io/t9by7/).

570





572 Figure 1: Bias manipulations affect explicit perceptual reports. (a) The receiver 573 operating characteristic (ROC) showing individual z-transformed hit and false alarm rates. 574 The two black lines with slope 1 are the predictions of an equal-variance model for each 575 experiment (Expt. 1 is the upper black line). The data have slopes consistently less than one. 576 suggesting that the distribution of sensory evidence has higher variance when the target is 577 present rather than absent. (b) Signal detection models that account for the empirical hit and 578 false alarm rates. These show probability distributions of sensory evidence E on target-579 absent trials (light gray distributions) and target-present trials (darker distributions). The 580 standard deviations of the target-present distributions were derived from the average ROC 581 slopes in panel a. The blue and red vertical lines are the mean empirical criteria (computed 582 from false alarm rates) in the liberal and conservative conditions, respectively. (c) Individual 583 participants' detection sensitivity d', assuming that the sensory evidence distributions have 584 unequal variance as modeled in panel b. Experiment 1 is in filled circles. Experiment 2 in 585 open circles. Thin gray lines connect points from the same participant. The horizontal 586 positions of individual data points are jittered to avoid total overlap, but points from the same 587 participant have the same relative jitter. The horizontal lines represent the means, with error 588 bars spanning the 68% bootstrapped confidence interval (approx. ±1SEM). (d) Individual 589 participants' decision bias computed as β for each participant, again assuming unequal 590 variance. Format as in panel c. Horizontal dotted lines are the optimal β for each condition 591 (dark blue = liberal; light red = conservative).

592

593 In sum, both bias manipulations had large effects on decision criteria for explicit judgements,

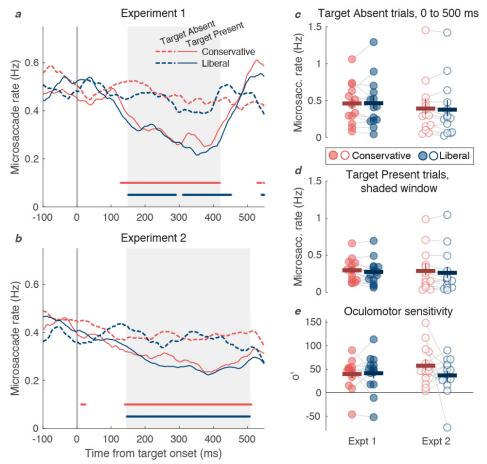
594 while sensitivity remained unaffected.

595 Microsaccade rates contingent on physical target presence: Bias manipulations do not affect 596 oculomotor freezing

597 Figures 2a and 2b show the mean microsaccade rates plotted as a function of time relative 598 to target onset. The target, when present, was flashed at time point 0. In both experiments 599 we observed oculomotor freezing on target-present trials (solid lines): the microsaccade rate 600 begins to drop roughly 130-150 ms after stimulus onset, and then returns to baseline 300-601 400 ms later. The key question is whether microsaccade rates differ between the liberal and 602 conservative bias conditions. The *distinct-criteria hypothesis* predicts no difference. The 603 shared-criterion hypothesis, which posits that oculomotor freezing is linked to explicit report 604 decisions, predicts a greater drop in microsaccade rates on target-present trials of the liberal 605 condition, in which the participant reports "present" more often. The data do not support the 606 shared-criterion hypothesis. Although the mean rate in the liberal condition (blue line) dips 607 slightly lower than in the conservative condition (red line), that effect is small and not 608 consistent across participants.

609 To simplify this analysis and maximize power, we integrated microsaccades over two key 610 time windows: 0 to 500 ms for target-absent trials and the window of significant oculomotor 611 freezing for target-present trials (shaded windows in Figures 2a and 2b; see Methods). In 612 Experiment 1, the window of significant freezing was from 149 ms to 421 ms, and in 613 Experiment 2 it was 145 to 509 ms. As shown in **Figures 2c** and **2d**, there were no reliable 614 effects of bias condition on the mean microsaccade rates in these time windows. We 615 evaluated the effects both as mean differences (L - C), where L is the rate on liberal trials and 616 C on conservative trials) and as modulation indices [(L - C)/(L + C)] that adjust for individual 617 differences in overall microsaccade rate. With one exception, none of those effects were 618 significant: 95% CIs include 0, and Bayes Factors (BFs) support the null hypothesis at least 619 2:1 (BFs<0.5). The one exception is for target-absent trials in Experiment 2: when the effect 620 is expressed as a modulation index, the baseline microsaccade rate was slightly but 621 significantly lower on liberal than conservative trials (mean index = -0.09, 95% CI = [-0.17 -622 0.02]; BF=1.35. The mean difference was only -0.02 Hz (95% CI = [-0.04 0.03]; BF=0.37).

623



624 625 Figure 2: Bias manipulations do not affect overall microsaccade rates on target-626 present and target-absent trials. (a,b) Mean microsaccade rates as a function of time 627 relative to target onset in Experiments 1, for target-absent trials (dotted lines) and target-628 present trials (solid lines). The horizontal lines at the bottom of each plot indicate time points 629 when the rate on target-present trials is significantly different from the rate on target-absent 630 trials (corrected p < 0.05). The gray region of the background indicates the time window when 631 the rate was significantly reduced on target-present trials in both conditions. (c) Mean 632 microsaccade rates on target-absent trials in the time window between 0 and 500 ms. 633 Format as in Figure 1a. (d) Mean microsaccade rates on target-present trials in the time 634 windows with significant inhibition in both conditions (shaded portions in panels a and b). 635 There are no significant effects of bias condition. (e) Oculomotor sensitivity (o'), a measure of 636 the difference in microsaccade rates between target-present and target-absent trials over the 637 entire interval 0 to 500 ms. There are no significant effects of bias condition. 638

- 639 To combine across experiments, we entered these data into linear mixed effects models
- 640 (LMEs), with fixed effects for condition, experiment, and their interaction, as well as random
- 641 effects for participant. We fit one such model for the target-absent trials and another for the
- 642 target-present trials. The effect of condition was negligible in both analyses (0.006 and 0.02
- 643 Hz, respectively), and not significant (both p>0.10; both BF<0.5). There were no effects of
- 644 experiment nor interaction between experiment and condition (all p>0.5).

645 We also computed oculomotor sensitivity (*o*) as a measure of the strength of oculomotor

- 646 freezing (White and Rolfs 2016) (Figure 2e), comparable to d'. In both experiments, o' did
- not differ significantly between bias conditions: 95% CIs were far from excluding 0 and Bayes
- 648 Factors supported the null hypothesis (all BFs<0.5). If anything, the effect in Experiment 2
- 649 (conservative > liberal) went in the direction opposite predicted by the shared criterion
- hypothesis, but was not significant (mean modulation index = -0.32, 95% CI = [-1.55 0.11]).
- An LME combining across experiments found no effect of condition (p=0.32, 95% CI = [-28.4]
- 9.5]; BF=0.30) and no main effect of experiment nor interaction (both p>0.2).
- Altogether, the microsaccade rates in this first analysis are consistent with the distinct-criteria
- 654 hypothesis: oculomotor freezing is independent of bias manipulations that affect explicit

655 perceptual reports. Next, we sorted the data further by the participant's report on each trial.

- 656 Based on our prior study (White and Rolfs 2016), we predicted more oculomotor freezing on
- trials when the participant reports seeing a stimulus than when they don't, but the magnitude
- of that effect may depend on the bias condition.
- 659 Microsaccade rates contingent on explicit perceptual reports: Oculomotor freezing is stronger 660 in conservative than liberal bias conditions

661 When we analyze trials separately according to whether the participant reported target 662 presence or absence, the shared-criterion hypothesis predicts no effect of bias condition. 663 The observer's ultimate decision is the same on liberal hit trials as on conservative hit trials. 664 so the prevalence of oculomotor freezing should be the same. In contrast, the distinct-criteria 665 hypothesis predicts an effect of bias condition: when considering only trials in which the 666 observer reports target presence (hits and false alarms), microsaccade rates should be lower 667 in the conservative condition than liberal condition. This is because in the conservative 668 condition, the sensory evidence must be stronger for the participant to report presence, and 669 therefore it is also likely to trigger oculomotor freezing. In the liberal condition, some explicit 670 reports of target presence are guesses with low sensory evidence, which will not exceed the 671 criterion for oculomotor freezing, so microsaccade rates should be higher.

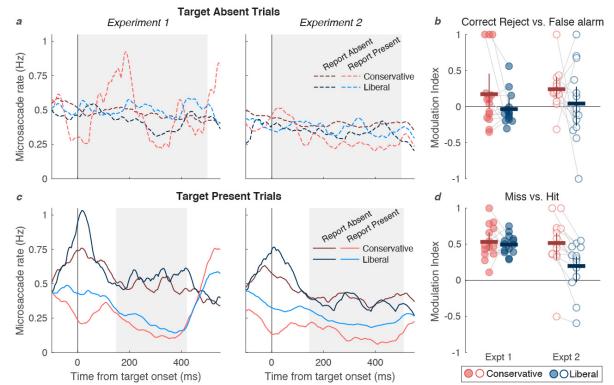
- Figure 3a plots the mean microsaccade rates on target absent trials, separated by bias
 condition and the participant's explicit report of whether a target was present or not (correct
 reject trials in dark lines, false alarm trials in bright lines). In a prior study (White and Rolfs
- 675 2016), we found that microsaccade rates were lower on false alarm than correct reject trials,

consistent with the notion that a spurious sensory signal triggered both an explicit false alarm
and oculomotor freezing. The distinct-criteria hypothesis predicts that effect (the relative
inhibition of microsaccades on false alarm trials) should be weakened in the liberal condition,
when many false alarms are guesses without a sensory signal strong enough to inhibit
microsaccades.

681 To test these predictions, we integrated microsaccade rates over the 0 to 500 ms time 682 window (shaded region) and then computed the effect of explicit report as a modulation 683 index: (CR – FR) / (CR + FR), where CR is the microsaccade rate on correct reject trials and 684 FR is the microsaccade rate on false alarm trials. The occurrence of oculomotor freezing on 685 false alarm trials predicts a positive index. In addition, the distinct-criteria hypothesis predicts 686 a larger index in the conservative compared to the liberal condition. The mean indices are 687 plotted in Figure 3b and listed in Table 2 with 95% CIs and BFs. Only in the conservative 688 condition of Experiment 2 was the effect of report significant. According to a linear mixed 689 effects model that combined experiments, there was a small but significant difference 690 between microsaccade rates on correct reject vs. false alarm trials (mean index = 0.11, CI = 691 [0.004 0.209], p=0.04, BF=1.4), a marginal effect of bias condition (index 0.2 larger in the 692 conservative condition, CI = [0.002 0.41], p=0.053; BF=1.28), and no effect of experiment nor 693 interaction (both p>0.4, BF<0.25). All told, the data in Figure 3b support our previous finding 694 that false alarms are associated with inhibition of microsaccades, and are consistent with the 695 distinct-criteria hypothesis. However, this analysis is limited due to the small number of false 696 alarm trials in the conservative condition (on average across participants, only 20 trials in 697 Experiment 1 and 70 in Experiment 2). The target-present trials provide supporting evidence.

698 Figure 3c plots microsaccade rates on target-present trials. These traces diverge around 699 stimulus onset (i.e., 0 ms) due to the reductive effect of microsaccades on perceptual 700 sensitivity (Rolfs 2009; Scholes et al. 2018; White and Rolfs 2016; Zuber et al. 1964): a 701 microsaccade that occurs close in time to the stimulus onset can make the participant miss 702 the stimulus, thus miss trials are associated with a peak in the microsaccade rate near time 703 0. That peak is especially large in the liberal condition, when misses are less frequent and 704 require a definite lack of target evidence. Conversely, hits are associated with fewer 705 microsaccades near the time of stimulus onset, and thus there is a dip in microsaccade rate 706 on hit trials. That dip is larger in the conservative condition, when hits require high certainty 707 and would otherwise be turned to misses by microsaccades. We previously confirmed that 708 the drop in microsaccade rates on hit trials ~150-400 ms post-stimulus is not an artifact of the

- 709 divergent dips and peaks observed around 0 ms due to saccadic suppression of perception
- 710 (White and Rolfs 2016).



711 712 Figure 3: Microsaccade rate signatures as a function of bias condition and explicit 713 **report outcome**. (a) Mean rates as a function of time on target absent trials, separated by 714 bias condition and by whether the participant reported target absent (correct reject trials, dark 715 lines) or target present (false alarm trials, bright lines). Note there are very few false alarm 716 trials in the conservative condition (bright red lines) (b) The mean modulation indices 717 comparing microsaccade rates on correct reject trials and false alarm trials, integrated over 0 718 to 500 ms (shaded interval in panel a). Format as in Figure 1a, except the error bars are 719 bootstrapped 95% confidence intervals to highlight significant deviations from zero. The 720 overall effect of perceptual report is significant, and marginally higher on conservative than 721 liberal trials. (c) Mean microsaccade rates on target present trials, separated by bias 722 condition and by whether the participant reported target absent (miss trials, dark lines) or 723 reported target present (hit trials, bright lines), (d) The mean indices comparing 724 microsaccade rates on miss and hit trials, integrated over the intervals with significant 725 stimulus-induced inhibition (shaded in panel c). Microsaccade rates are significantly lower on 726 hit than miss trials, and that effect is significantly larger on conservative than liberal trials. 727 728 Our current research question focuses on the later time period, starting roughly 150 ms post-

- stimulus, when stimulus detection is associated with inhibition of microsaccades. We tested
- 730 whether that effect of perceptual report (misses vs hits) is equal in the two bias conditions.
- 731 The distinct-criteria hypothesis predicts greater inhibition on hit trials of the conservative

condition, because conservative hits are "purer" (i.e., they contain fewer lucky guesses) and
 require a strong sensory signal that is also likely to trigger oculomotor freezing.

734 Indeed, the microsaccade rate dips lower on hit trials of the conservative condition (Figure

- 735 **3c**, light red lines) than of the liberal condition (light blue lines). To summarize these effects,
- 736 we integrated microsaccade rates over the time window with significant inhibition (shaded
- windows in **Figures 2a**, **2b**, and **3b**). For each bias condition we then computed the effect of
- explicit detection as a modulation index: (M-H)/(M+H), where M is the microsaccade rate on
- miss trials and H is the rate on hit trials. The effect of explicit detection was significant (95%
- 740 CI of the index excludes 0) in all conditions except the liberal condition of Experiment 2 (see
- 741 **Table 3**). According to a linear mixed effects model, that modulation index was significantly
- Iarger in the conservative than liberal condition (by 0.18 on average, CI = [0.08 0.14],
- p=0.0004; BF=34.0). This is strong evidence that correct reports of target presence in the
- conservative condition are associated with stronger inhibition of microsaccades than in the
- 745 liberal condition. The effect of bias condition was also larger in Experiment 2 than
- Experiment 1 (interaction between condition and experiment, p=0.004; BF=6.32).

		Correct reject - False alarm			Miss - Hit		
	Condition	Modulation index	Index 95% CI	BF	Modulation index	Index 95% CI	BF
Expt. 1	Conservative	0.17 (0.13)	[-0.039 0.437]	0.58	0.53 (0.06)	[0.429 0.657]	1.4x10 ⁴
	Liberal	-0.03 (0.06)	[-0.121 0.116]	0.41	0.50 (0.04)	[0.433 0.566]	2.6x10 ⁶
Expt. 2	Conservative	0.24 (0.08)	[0.128 0.403]	7.47	0.52 (0.10)	[0.248 0.671]	197.6
	Liberal	0.04 (0.14)	[-0.226 0.319]	0.27	0.20 (0.09)	[-0.008 0.333]	1.68

747 Table 3: Effects of perceptual report on microsaccade rates, expressed as modulation

748 **indices.** The columns labeled "Modulation index" contain the mean, with standard error

across participants in parentheses. The 95% CIs are derived from bootstrapping.

750 These data consistently support the distinct-criteria hypothesis: oculomotor freezing is

triggered when a sensory signal crosses a threshold that is independent of the participant's

decision bias. The sensory signal is more likely to have crossed that oculomotor threshold on

- hit trials of the conservative condition, when the criterion for explicit report is higher, than on
- hit trials of the liberal condition. Thus, when the participant was induced to adopt a more

conservative decision bias, explicit detection of the stimulus was associated with morepronounced oculomotor freezing.

757 **DISCUSSION**

Detecting potentially relevant stimuli in the environment is a fundamental task of perceptual
 systems. Our data suggest that although sensory input is continuous and noisy, the brain

switches into a qualitatively different state when there is sufficient evidence that a target is

present. Passing this threshold gives rise to a conscious percept *and* an involuntary pause of

saccadic eye movements (that is, oculomotor freezing). A pause in microsaccades can be

considered the oculomotor system's "report" that it detected a stimulus. The participant's

decision to respond voluntarily to the stimulus – for instance, by pressing a button –

depends on the conscious percept as well as potential rewards and expectations.

766 Visual stimulus detection therefore has three consequences that are of interest to the present

investigation: a conscious percept, a decision to report stimulus presence, and oculomotor

768 freezing. It is crucial that we understand how those three consequences relate in terms of

neural and cognitive mechanisms. Provided oculomotor freezing is indeed a proxy for

conscious perception (as we argue below), researchers would be equipped with a "no-report"

paradigm to investigate the neural correlates of consciousness (Tsuchiya et al. 2015) without

772 interference from explicit cognitive tasks.

773 In five independent experiments across this study and a previous one (White and Rolfs

2016), we consistently found that explicit reports and oculomotor freezing covary: the eyes

only freeze in response to stimuli that the person reports seeing. To explain that covariation,

here we manipulated the likelihood of explicit reports of stimulus presence. When rewards

and penalties were greater on target-present than target-absent trials (Experiment 1), or

when the target probability was known to be high (Experiment 2), participants adopted a

liberal decision criterion, reporting target presence much more often than in the opposite

780 (conservative) conditions (**Figure 1**).

In contrast, the magnitude of the drop in microsaccade rates just after stimulus onset showed little to no effect of our bias manipulations (**Figure 2**). We need not rely only on that null result, however, because we also found effects of the bias condition when splitting the trials according to the explicit report (**Figure 3**). The difference in microsaccade rates between hit and miss trials, which indexes the link between explicit reports and oculomotor freezing, was 786 larger in the conservative than the liberal condition. Our interpretation is that when

787 participants make conservative decisions, they only report sensations that are strong enough

to also trigger oculomotor freezing. In contrast, when participants make liberal decisions,

they often make strategic guesses that a stimulus was present, even when the sensory

signal was weak and oculomotor freezing was not triggered.

791 We therefore reject the shared-criterion hypothesis and support the distinct-criteria

hypothesis (described in the Introduction). The criteria in question specify the magnitude of

sensory evidence required to trigger a response. There is one criterion for explicitly reporting

stimulus presence, and it can be shifted to maximize rewards. There is also a distinct

riterion for inhibiting eye movements, which is relatively stable and not affected by shifts of

796 decision criterion.

797 This conclusion is consistent with studies that predicted individual perceptual contrast

thresholds based on microsaccade patterns that were measured while the participant did not

resplicitly respond to the stimuli (Bonneh et al. 2015; Denniss et al. 2018; Scholes et al.

800 2015). These studies show that oculomotor freezing is not related to response preparation.

801 However, participants in those studies either had to silently count the stimuli (Bonneh et al.

802 2015), or prepare to respond on a random subset of trials (Denniss et al. 2018; Scholes et al.

803 2015), so they were likely making covert decisions about each stimulus. Therefore, decision-

804 making processes could have contributed to oculomotor freezing in those data. Our data help

805 isolate the link between perception and oculomotor freezing.

806 A key feature of our theory is that oculomotor freezing is all-or-none, not graded. In a prior

study (White and Rolfs 2016), we varied the visibility of a target grating by varying its

808 luminance contrast, or by adapting the observer to the same or different orientation.

809 Considering all target-present trials, the degree of oculomotor freezing scaled with explicit d'.

810 However, when considering only hit trials, oculomotor freezing was equivalently across all

811 contrast levels and adaptation states. Intense stimuli had no effect on eye movements if the

812 observer missed them, and faint stimuli were accompanied by full-fledged inhibition provided

813 they were detected. We found similar patterns in the new data reported above, providing

814 consistent support that oculomotor freezing is a discrete all-or-none reflex that occurs if and

815 only if a stimulus is consciously detected. Such a model is reminiscent of "high threshold

theory," which has been largely discredited (Swets 1961). Standard signal detection theory,

817 which has been more successful, assumes no threshold for detection other than the

observer's flexible decision criterion. In that regard, the data presented here are not fullyconsistent with standard signal detection theory.

Our data are, at least in part, consistent with the "global neuronal workspace theory" of consciousness. It proposes that a stimulus becomes reportable when "ignites" sustained neural communication across the brain (Mashour et al. 2020). Recent electrophysiological data suggest that ignition occurs when activity in frontal cortex, not sensory cortex, reaches a threshold, roughly 200 ms after stimulus onset (Van Vugt et al. 2018). We might speculate that such an 'ignition' is related to oculomotor freezing, but it occurs later than the initial drop in microsaccade rates.

827 For now, we consider two possibilities for how oculomotor freezing relates to the conscious

828 experience of the stimulus that triggers it. Both are compatible with the distinct-criteria

829 hypothesis described in the Introduction. (1) Oculomotor freezing and conscious perception

are tightly coupled, because they are both triggered when the same sensory signal crosses

the same threshold. That threshold is not affected by bias manipulations, unlike the criterion

832 for explicit reports. (2) Oculomotor freezing and conscious perception can be dissociated,

833 because the threshold for oculomotor freezing is stable but the threshold for conscious

834 perception is affected by bias manipulations, along with the decision criterion. While our data

reveal that explicit reports and oculomotor freezing have distinct criteria, they are consistent

836 with both possibilities regarding conscious perception.

837 We nonetheless favor the first possibility: oculomotor freezing and conscious perception are 838 coupled. This hypothesis must also assume that the bias manipulations (payoffs and 839 probability cues) affect decisions at a post-perceptual stage. Specifically, in the liberal 840 conditions, observers reported "yes" more often because doing so maximized rewards, not 841 because they actually saw the target more often. That is why the difference in microsaccade 842 rates between hit and correct reject trials is weaker in the liberal than conservative condition. 843 The implication is that oculomotor freezing provides an implicit index of conscious perception 844 that is free of bias.

845 However, this conclusion fails if the bias manipulations do affect conscious perception (i.e.,

846 the second possibility). There is some neurophysiological evidence that expectations, as

847 manipulated by the probability cues in Experiment 2, can affect sensory processing (De

Lange et al. 2018; Pajani et al. 2015). One theory is that expecting a stimulus evokes a

849 "template" in neural populations that prefer the expected features (Kok et al. 2014, 2017). In

850 contrast, one fMRI study concluded that payoff and probability manipulations recruit frontal

and parietal brain regions involved in decision-making to shift the starting point of evidence

accumulation, similar to a criterion shift (Mulder et al. 2012). The existing behavioral

853 evidence is also ambiguous. One study argued that expectation improves detection by

elevating the baseline of "signal-selective units" (Wyart et al. 2012). Another found that

probability cues presented *after* the stimulus had similar effects as cues presented *before* the

stimulus, in favor of a post-perceptual criterion shift (Bang and Rahnev 2017). It remains a

857 matter of discussion, therefore, whether expectations affect conscious perception or decision

processes (Press et al. 2020; Rungratsameetaweemana et al. 2018;

859 Rungratsameetaweemana and Serences 2019; Summerfield and Egner 2016). The simplest

860 model that explains our data assume that they affect decision processes only.

861 We must also note that the results favoring the distinct-criteria hypothesis are clearer in

862 Experiment 2 (which manipulated expectations) than Experiment 1 (which manipulated

rewards). Indeed, other researchers have found that probability manipulations have stronger

864 effects on perceptual decisions than reward manipulations do (Leite and Ratcliff 2011;

865 Mulder et al. 2012; Simen et al. 2009). In our case there are several possible explanations:

866 first, there were greater individual differences in explicit report criteria in Experiment 1

867 (Figure 1d), perhaps due to variable interpretations of, or value placed in, the rewards. Such

868 individual differences may have added noise to the microsaccade data as well. Second,

overall *d'* levels were higher in Experiment 1 than 2 (Figure 1c). The bias manipulations are

870 likely to have greater effects when the target is difficult to detect. Third, it may be that

871 expected rewards affect decisions at a post-perceptual stage, whereas expectations affect

perception, as discussed above. In that case, the explicit reports in Experiment 1 were less

873 driven by the sensory signal, thus showing a less clear relationship with oculomotor freezing.

In contrast, Experiment 2 could be explained by a model in which expecting a stimulus

875 lowers the sensory threshold for conscious perception, but does not affect the threshold for

876 oculomotor freezing. While this model would explain the smaller difference in microsaccade

rates between hit and miss trials in the liberal condition (**Figure 3d**), it is comparably

878 complicated.

We may also consider the probability cues of Experiment 2 in light of the "predictive coding" framework (De Lange et al. 2018). A target in the "conservative" condition is unexpected, and thus should produce a larger prediction error. If oculomotor freezing is a "surprise" response,

then we would have predicted a larger drop in microsaccades in target-present trials of the

883 conservative condition than the liberal condition. We did observe that, but only on hit trials

884 (Figure 3c). The predictive coding framework may therefore help explain oculomotor

885 freezing.

886 Altogether, the most parsimonious explanation for our results is that oculomotor freezing and

887 conscious detection share a common sensory threshold. This threshold is distinct from the

888 decision criterion to report a stimulus, which is shifted by weighted payoffs and expectations.

889 The alternate explanation, that the threshold for conscious detection can diverge from the

890 threshold for oculomotor freezing, is more complicated. It must either postulate an additional

891 free parameter, for a total of three sensory thresholds/criteria, or it must assume that the

decision criterion is also the threshold for perception and thus bias manipulations truly affect

893 perception. To the extent that the more parsimonious explanation stands, oculomotor

894 freezing provides a valuable tool to measure conscious perception free of the influence of

895 decision bias, and without requiring explicit reports.

896

897

898 References

- Abeles D, Amit R, Tal-Perry N, Carrasco M, Yuval-Greenberg S. Oculomotor inhibition
- 900 precedes temporally expected auditory targets. *Nat Commun* 11: 1–12, 2020.
- 901 Amit R, Abeles D, Carrasco M, Yuval-Greenberg S. Oculomotor inhibition reflects
- 902 temporal expectations. *Neuroimage* 184: 279–292, 2019.
- 903 Badde S, Myers CF, Yuval-Greenberg S, Carrasco M. Oculomotor freezing reflects tactile
- 904 temporal expectation and aids tactile perception. *Nat Commun* 11: 1–9, 2020.
- 905 **Bang JW**, **Rahnev D**. Stimulus expectation alters decision criterion but not sensory signal in
- 906 perceptual decision making. *Sci Rep* 7: 1–12, 2017.
- 907 **Benjamini Y**, **Hochberg Y**. Controlling the False Discovery Rate: A Practical and Powerful
- 908 Approach to Multiple Testing [Online]. J R Stat Soc Ser B 90: 289–300,
- 909 1995http://www.pnas.org/content/90/12/5718.short [17 Feb. 2012].
- 910 Betta E, Turatto M. Are you ready? I can tell by looking at your microsaccades. *Neuroreport*911 17: 1001–1004, 2006.
- Bonneh YS, Adini Y, Polat U. Contrast sensitivity revealed by microsaccades. *J Vis* 15: 1–
 12, 2015.
- 914 **Brainard DH**. The psychophysics toolbox. *Spat Vis* 10: 443–446, 1997.
- 915 **Cornelissen FW**, **Peters EM**, **Palmer J**. The eyelink toolbox: Eye tracking with MATLAB and
- 916 the psychophysics toolbox. *Behav Res Methods, Instruments, Comput* 34: 614–617, 2002.
- 917 **Crapse TB**, Lau H, Basso MA. A Role for the Superior Colliculus in Decision Criteria.
- 918 *Neuron* 97: 181-194.e6, 2018.
- 919 **Denison RN**, **Yuval-Greenberg S**, **Carrasco M**. Directing voluntary temporal attention
- 920 increases fixational stability. *J Neurosci* 39: 353–363, 2019.
- 921 Denniss J, Scholes C, McGraw P V., Nam SH, Roach NW. Estimation of contrast
- 922 sensitivity from fixational eye movements. *Investig Ophthalmol Vis Sci* 59: 5408–5416, 2018.
- 923 Efron B, Tibshirani R. An Introduction to the Bootstrap. New York: Chapman and Hall,
- 924 1993.

- 925 Engbert R, Kliegl R. Microsaccades uncover the orientation of covert attention. *Vision Res*
- 926 43: 1035–1045, 2003.
- 927 Engbert R, Mergenthaler K. Microsaccades are triggered by low retinal image slip. *Proc*
- 928 Natl Acad Sci 103: 7192–7197, 2006.
- 929 Hafed ZM. Mechanisms for generating and compensating for the smallest possible
- 930 saccades. *Eur J Neurosci* 33: 2101–2113, 2011.
- 931 Hafed ZM, Goffart L, Krauzlis RJ. A neural mechanism for microsaccade generation in the
- 932 primate superior colliculus. *Science (80-)* 323: 940–943, 2009.
- 933 Hafed ZM, Ignashchenkova A. On the dissociation between microsaccade rate and
- 934 direction after peripheral cues: microsaccadic inhibition revisited. J Neurosci 33: 16220-
- 935 16235, 2013.
- 936 Kaernbach C. A single-interval adjustment-matrix (SIAM) procedure for unbiased adaptive
- 937 testing [Online]. J Acoust Soc Am 88: 2645–2655,
- 938 1990http://link.aip.org/link/jasman/v88/i6/p2645/s1 [4 Oct. 2012].
- Mass RE, Raftery AE. Bayes Factors. J Am Stat Assoc 90: 773–795, 1995.
- 940 Kok P, Failing MF, de Lange FP. Prior expectations evoke stimulus templates in the primary
- 941 visual cortex. *J Cogn Neurosci* 26: 1546–1554, 2014.
- 942 Kok P, Mostert P, De Lange FP. Supporting Information for: Prior expectations induce
- 943 prestimulus sensory templates. *Proc Natl Acad Sci*, 2017.
- 944 **Kubovy M**. A possible basis for conservatism in signal detection and probabilistic
- 945 categorization tasks. *Percept Psychophys* 22: 277–281, 1977.
- 946 **De Lange FP**, **Heilbron M**, **Kok P**. How Do Expectations Shape Perception? Perceptual
- 947 Consequences of Expectation. *Trends Cogn Sci* 22: 764–779, 2018.
- 948 Leite FP, Ratcliff R. What cognitive processes drive response biases? A diffusion model
- 949 analysis. *Judgm Decis Mak* 6: 651–687, 2011.
- 950 Macmillan NA, Creelman CD. Detection Theory: A User's Guide. Mahway, New Jersey:
- 951 Lawrence Erlbaum Associates, 2005.
- 952 Mashour GA, Roelfsema P, Changeux JP, Dehaene S. Conscious Processing and the
- 953 Global Neuronal Workspace Hypothesis. *Neuron* 105: 776–798, 2020.

- 954 Mulder MJ, Wagenmakers EJ, Ratcliff R, Boekel W, Forstmann BU. Bias in the brain: A
- 955 diffusion model analysis of prior probability and potential payoff. *J Neurosci* 32: 2335–2343,
- 956 2012.
- 957 Otero-Millan J, Macknik SL, Langston RE, Martinez-Conde S. An oculomotor continuum
- 958 from exploration to fixation. *Proc Natl Acad Sci U S A* 110: 6175–6180, 2013.
- 959 Pajani A, Kok P, Kouider S, de Lange FP. Spontaneous activity patterns in primary visual
- 960 cortex predispose to visual hallucinations. *J Neurosci* 35: 12947–12953, 2015.
- 961 **Pelli DG**. The VideoToolbox software for visual psychophysics: Transforming numbers into
- 962 movies. *Spat Vis* 10: 437–442, 1997.
- 963 Press C, Kok P, Yon D. The Perceptual Prediction Paradox. *Trends Cogn Sci* 24: 13–24,
 964 2020.
- 965 Reingold EM, Stampe DM. Saccadic inhibition in voluntary and reflexive saccades. *J Cogn* 966 *Neurosci* 14: 371–88, 2002.
- 967 **Rolfs M**. Microsaccades: small steps on a long way. *Vision Res* 49: 2415–2441, 2009.
- 968 Rolfs M, Kliegl R, Engbert R. Toward a model of microsaccade generation: The case of
 969 microsaccadic inhibition. *J Vis* 8(11):5: 1–23, 2008.
- 970 **Rolfs M**, Laubrock J, Kliegl R. Shortening and prolongation of saccade latencies following
- 971 microsaccades. *Exp brain Res* 169: 369–76, 2006.
- 972 Rouder JN, Morey RD, Speckman PL, Province JM. Default Bayes factors for ANOVA
- 973 designs. J Math Psychol 56: 356–374, 2012.
- 974 Rouder JN, Speckman PL, Sun D, Morey RD, Iverson G. Bayesian t tests for accepting
- and rejecting the null hypothesis. *Psychon Bull Rev* 16: 225–237, 2009.
- 976 Rucci M, Poletti M. Control and Functions of Fixational Eye Movements. *Annu Rev Vis Sci*977 1: 499–518, 2015.
- 978 Rungratsameetaweemana N, Itthipuripat S, Salazar A, Serences JT. Expectations do not
- alter early sensory processing during perceptual decision-making. *J Neurosci* 38: 5632–
 5648, 2018.
- 981 **Rungratsameetaweemana N**, Serences JT. Dissociating the impact of attention and
- 982 expectation on early sensory processing. *Curr Opin Psychol* 29: 181–186, 2019.

- 983 Scholes C, McGraw P V., Roach NW. Selective modulation of visual sensitivity during
- 984 fixation. *J Neurophysiol* 119: 2059–2067, 2018.
- 985 Scholes C, Mcgraw P V, Nystrom M, Roach NW. Fixational eye movements predict visual
- 986 sensitivity. *Proc R Soc B* 282: 20151568, 2015.
- 987 Simen P, Contreras D, Buck C, Hu P, Holmes P, Cohen JD. Reward Rate Optimization in
- 988 Two-Alternative Decision Making: Empirical Tests of Theoretical Predictions. J Exp Psychol
- 989 *Hum Percept Perform* 35: 1865–1897, 2009.
- 990 **Summerfield C**, **Egner T**. Feature-Based Attention and Feature-Based Expectation. *Trends*
- 991 *Cogn Sci* 20: 401–404, 2016.
- 992 Swets JA. Is there a sensory threshold? *Science (80-)* 134: 168–177, 1961.
- 993 Swets JA, Tanner WP, Birdsall TG. Decision Processes In Perception. *Psychol Rev* 68:
- 994 301–340, 1961.
- 995 **Tsuchiya N, Wilke M, Frässle S, Lamme VAF**. No-Report Paradigms: Extracting the True
- 996 Neural Correlates of Consciousness. *Trends Cogn Sci* xx: 1–14, 2015.
- 997 Van Vugt B, Dagnino B, Vartak D, Safaai H, Panzeri S, Dehaene S, Roelfsema PR. The

998 threshold for conscious report: Signal loss and response bias in visual and frontal cortex.

999 Science (80-) 360: 537–542, 2018.

- White AL, Rolfs M. Oculomotor inhibition covaries with conscious detection. *J Neurophysiol*1101 116: 1507–1521, 2016.
- 1002 Widmann A, Engbert R, Schröger E. Microsaccadic Responses Indicate Fast
- 1003 Categorization of Sounds: A Novel Approach to Study Auditory Cognition. *J Neurosci* 34:
- 1004 11152–11158, 2014.
- 1005 Wyart V, Nobre AC, Summerfield C. Dissociable prior influences of signal probability and
- 1006 relevance on visual contrast sensitivity. *Proc Natl Acad Sci U S A* 109: 3593–3598, 2012.
- 1007 Zuber BL, Crider A, Stark L. Saccadic suppression associated with microsaccades. *Q Prog* 1008 *Rep* 74: 1964, 1964.
- 1009
- 1010
- 1011

1012 **Supplementary Data:** Two supplementary data figures can be viewed here:

1013 https://osf.io/t9by7/.

1014 Acknowledgments

- 1015 We are grateful to Michael Grubb, Jan-Nikolas Klanke and Dobromir Rahnev for comments
- 1016 on this manuscript, to Jan-Nikolas Klanke for data collection, and to Richard Schweitzer for
- 1017 technical assistance.

1018 Funding:

- 1019 The Humboldt University Talent Travel Award (AW, JM)
- 1020 Deutsche Forschungsgemeinschaft (DFG) grants RO3579/8-1 and RO3579/12-1 (MR).
- 1021 National Institutes of Health grant K99 EY029366 (AW).
- 1022

1023 Author contributions:

- 1024 Conceptualization: AW, JM, MR
- 1025 Methodology: AW, JM, MR
- 1026 Investigation: AW, MR
- 1027 Software: AW, MR
- 1028 Resources: MR
- 1029 Formal analysis: AW
- 1030 Visualization: AW
- 1031 Supervision: MR
- 1032 Writing—original draft: AW
- 1033 Writing-review & editing: AW, MR
- 1034
- 1035 **Competing interests:** The authors have no financial for non-financial competing interests.
- 1036 1037
- 1038
- 1039
- 1040 1041
- 1042
- 1043
- 1044