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Supplemental Information

Varying Target Prevalence Reveals Two Dissociable Decision Criteria in Visual Search

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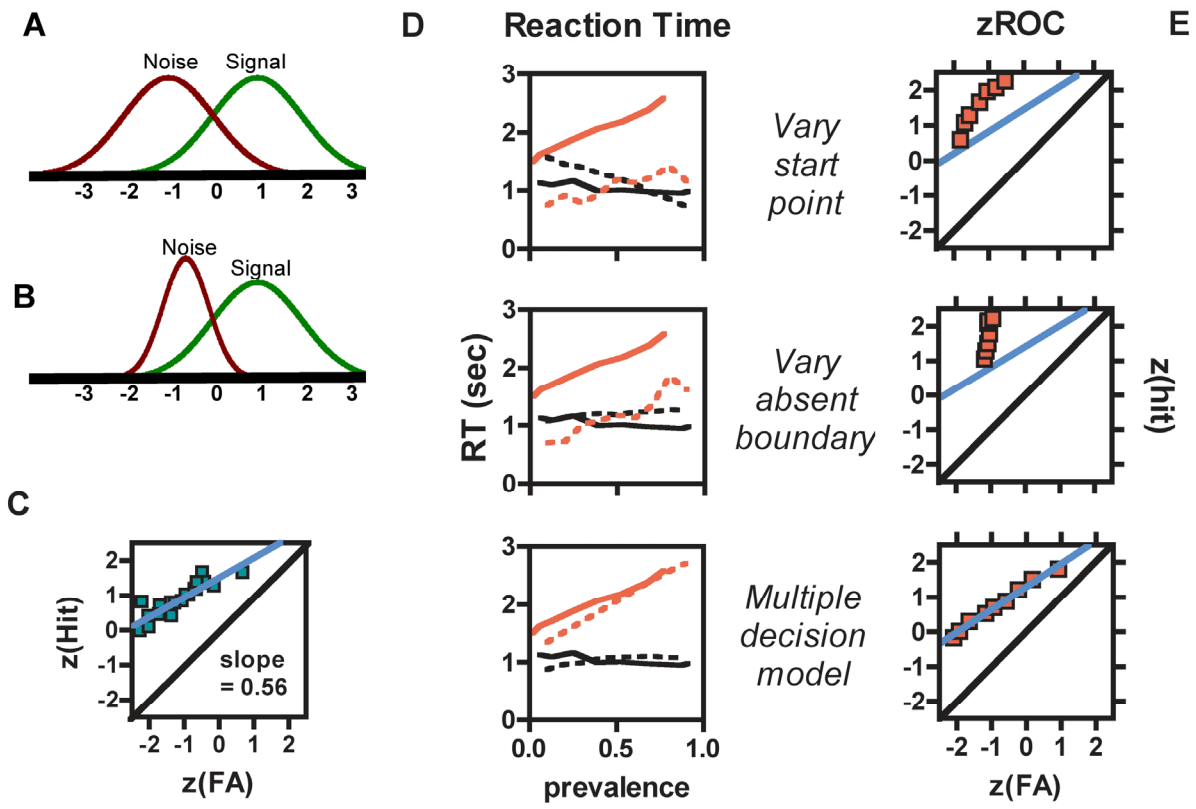

Figure S1.

Figure S1. Modeling the Effects of Prevalence

(A-C) Data in Figure 2 from Experiment Two (C) are consistent with an unequal variance signal detection model (B) not the more common equal-variance model (A).

(D and E) Three efforts to model these data. The top two, based on variations of single parameters of a standard diffusion model (Figure 3) perform poorly. The bottom row, based on variation of two parameters in the Multiple Decision Model (Figure 4), perform better.

(A) Calculations of sensitivity (d') and criterion are based on a standard signal detection model that assumes that the signal and noise distributions have equal variance as in S1A. Under these conditions, ROC curves are symmetrical around an axis connecting the upper left and lower right corners of a plot of the Hit rate against the False Alarm rate and zROC curves have a slope of 1.0 in a plot of z(Hit) against z(FA).

(B) Equal variance is merely an assumption and need not be the case. S1B shows a hypothetical situation in which the variance of the noise distribution is less than the variance of target distribution. This will produce asymmetrical ROCs and zROCs with slopes other than 1.0. This example produces a zROC slope less than 1.0.

(C) If the data from Figure 2A are replotted in z units on a zROC, the results reveal a zROC slope less than 1. In prior work, we have found that the simulated baggage task produces zROC slopes of about 0.6. Kundel [1] got a very similar slope in a study of lung cancer detection. Slopes less than 1.0 are also seen, for example, in some memory tasks [2, 3]. Moreover, some types of signal detection modeling of search for a target among multiple distractors lead to models in which the variance of the internal response to a target-absent trial is lower than the variance of the internal response to a trial with distractors and one target [4].

(D and E) We simulated the effects of prevalence described in the main text (see Supplementary Methods). The top two rows of S1D-E shows the effects of variations of either the start point or the lower boundary of a standard diffusion model (Figure 3) [5]. The last row shows results of varying criterion and quitting threshold in the Multiple Decision model of Figure 4.

Solid lines in Figure (D) show empirical RTs derived from Figure 2 (Black – target-present, gray/pink – target-absent). There is a substantial increase in target-absent RTs with rising target prevalence and little or no change in the faster present RTs. Dotted lines show simulated RT results for correct present trials (black) and correct absent trials (gray/pink). The multiple decision model performs best.

The patterns of simulated error rates are captured in the zROC graphs of S1E. The desired pattern, derived from Figure 2A is a trade-off of misses and false alarm errors producing a zROC with a slope near 0.6 as shown in S1C and reproduced as the blue/gray line in S1E. The "vary start point" and "vary absent boundary" versions of a simple diffusion model [5] do not capture the data. The multiple decision model performs well.

This modeling is intended to provide a qualitative indication of what type of model might account for the effects of prevalence. The results do not "disprove" diffusion models. They indicate that manipulation of a single parameter (in a diffusion model or elsewhere) is unlikely to successfully model the data in this paper. It is quite possible that a standard diffusion model could produce the correct pattern of results if two parameters covaried with prevalence. However, we believe that it is more plausible to see the search through the simulated bag as a series of 2AFC decisions about target presence plus a decision about search termination (the architecture shown in Figure 4 of the main paper). We allowed prevalence to change the criterion for the 2AFC decision and the threshold for the quitting decision.

Supplemental Experimental Procedures

Simulation of a 2AFC Diffusion Model (see Figure 3 and Top 2 Rows of Figures S1D and S1E)

To produce the results shown in the top two rows of Figure S1D and S1E, a standard diffusion model like that shown in Figure 3 was simulated. It had eight parameters (values used are given in parentheses but are not critical):

1) the rate of diffusion on target present trials (1)
2) the standard deviation of that rate (2)
3) the rate of diffusion on target absent trials (-0.5)
4) the standard deviation of that rate (2)
5) the starting point of the diffuser on each trial (0)
6) the standard deviation of that starting point (1)
7) the position of the target present border (6)
8) the position of the target absent border (-6).

The rule for the diffusion on a target-present trial was

$$d(t)=d(t-1)+N(1,2) \qquad (1)$$

On each time step of a target present trial, the value of the diffuser was updated by adding a random variable with a mean of 1 and s.d. of 2. This continued until the diffuser hit one of the borders. If it hit the upper bound, this was a correct target present response. If it hit the lower bound, this was a miss error. On target absent trials, the rule was

$$d(t)=d(t-1)+N(-0.5,2) \qquad (2)$$

and response was correct if the diffusion hit the lower bound and a false alarm error if it hit the upper bound. The RTs were converted from time steps to msec.

$$RTmsec = (TimeSteps * 120) \qquad (3)$$

The different rates of diffusion on present and absent trials capture the longer RTs on absent trials. This outcome could be accomplished in other ways (e.g. asymmetrical upper and lower bounds).

The point of the simulation is to examine model behavior as target prevalence changed. The critical aspects of the data to capture are 1) the change in criterion with prevalence, the lack of change in sensitivity, the change in correct absent RTs, and 2) the relative lack of change in correct present RTs. In the “vary start point” condition (top row of S1D and S1E) criterion change was simulated by a change in the starting position of the diffuser. This was a linear function of prevalence, varying from -4.4 to 4.4 as prevalence varied from 0.1 to 0.9. In the “vary absent boundary” condition (second row of S1D-E), change in correct absent RTs was simulated by a linear change in the position of the lower bound (-2.5 to -10.5). Again, the exact parameters are not critical. Changing the starting point shifts criterion in a reasonably correct manner. However, this produces the wrong pattern of RTs. Changing absent boundary alters the separation between upper and lower bounds. This changes sensitivity, contrary to the data.

Simulation of the Multiple-Decision Model (see Figure 4 and Last Row of Figure S1D and S1E)

To produce the results shown in the last rows of Figure S1D and S1E, a multiple-decision model like that shown in Figure 4 was simulated. It had eight parameters (values used are given in parentheses):

1) the sensitivity (d') of the internal 2AFC decision process (3.4)
2) the criterion (c) of the internal 2AFC decision process (varies from 1.22 to -0.22 as prevalence varied from 0.1 to 0.9)
3) the rate of diffusion of the quitting process (1)
4) the standard deviation of that rate (.5)
5) the starting point of the diffuser on each trial (0)
6) the standard deviation of that starting point (.5)
7) the position of the quitting threshold (varies from 8 to 20 as prevalence varied from 0.1 to 0.9)
8) the position of a quitting threshold that would produce a target present response (set to -100 so that this event never occurs).

At each time step, an item is "selected". This generates a random variable, distributed N(0,1) if it is a distractor and distributed N(3.4, 1) if it is a target. If that value is above criterion, the search is terminated with a "present" response. If not, search continues. The simulation assumed a fixed set size of 10. On each cycle, an item was sampled at random from the display with replacement [without memory for rejected items, [6] though this is not critical for the qualitative pattern of results in this case]. The rule for the quitting diffusion process was

$$q(t)=q(t-1)+N(1,0.5) \qquad (4)$$

The trial is terminated with an "absent" response if that cumulative value reaches the quitting threshold.

The criterion shift in the data is captured by a criterion shift in the decision made about each selected item in the course of the search. The large separation between target and distractor responses (d' = 3.4) is needed in order to keep the percentage of false alarms within bounds. In effect, the large sensitivity of the 2AFC decision means that, once an item is attended, the observer is quite sure if it is or is not at gun or a knife. Criterion varies linearly from 1.22 to -0.22 as prevalence rises from 0.1 to 0.9. The change in absent RTs is captured by a linear change in quitting threshold from 8 to 20 as prevalence rises from 0.1 to 0.9.

We do not want to make excessive claims for the multiple decision model with its serial selection of item after item. We think that complex search tasks that are extend over time are best understood as a series of 2AFC decisions. However, as noted, some version of a wholly parallel diffusion model can probably fit the data, too. Models that vary only one parameter seem unlikely to fit the data. For a diffusion model, moving just the start point or the "no" threshold does not produce good fits to the data. In results not shown here, we find that shifting only the 2AFC decision criterion or the quitting criterion in the multiple decision model does not work any better. Prevalence appears to have an impact on both the evaluation of candidate targets and the assessment of the appropriate time to quit.

Supplemental References

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