Supporting Information

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SI Discussion

Alternative Models. ***Random fixations model.*** One natural question is the extent to which the complex fixation patterns described here interact with the drift-diffusion process to affect choices. We investigated this question by simulating the model with the same parameters as before, but assuming that fixations are random and independent of the value or location after the first fixation. As shown in Fig. S1, we found no qualitative differences in the ability of the model to fit the trends, indicating that the aspects of the fixation process depicted in Fig. 4 are not driving the results. Goodness-of-fit measures are indicated in the figure legend; none fit significantly worse than the model that takes into account the more complex fixation pattern. This is not too surprising, because the fixation process described above is close to being random with respect to value, and so ignoring fine details of the fixation process only slightly changes the results compared with changing actual parameters or features of the model, as we have previously investigated in our binary choice work.

The random fixations model shown in Fig. S1 was simulated with the same parameters, in the same way as before, except for two differences. First, starting with the second fixation, fixation locations were determined by a 50/50 coin flip. Second, all fixation durations were independent of the liking ratings of the fixated items.

Best vs. average model. This alternative model was simulated in almost exactly the same way as our MSPRT (or "best vs. next" model) in the main text. The only difference is that the RDV signals for each option are defined as follows:

$$V_t^{left} = E_t^{left} - avg(E_t^{center}, E_t^{right})$$

$$V_t^{center} = E_t^{center} - avg(E_t^{left}, E_t^{right})$$

$$V_t^{right} = E_t^{right} - avg(E_t^{left}, E_t^{center})$$

Just as before, a choice is made as soon as one of these RDVs crosses a barrier with a constant value of +1. The resulting model fits are shown in Fig. S2.

SI Results

Parameter Comparison Between Binary and Trinary Choice Models. At first sight, the value of σ appears to be different from the one used in our binary study, where it took a value of 0.02. However, this difference is due to the fact that our previous model was written using the single RDV version of the model, instead of the two parallel accumulators. Therefore, the error term in the previous model reflected the sum of two independent noise terms, one for each alternative. Because the variance in normal models is additive, a $\sigma = 0.02$ in the old model is equivalent to a $\sigma = 0.014$ per noise term in the current model. In other words, these two values of σ lead to exactly the same amount of noise in both model specifications.

Why We See Extra Fixations in the Simulated Model. The model, on average, predicted 0.6 excess fixations per trial, compared with the data, which is due to the fact that we have to sample fixations from the empirical distribution of nonfinal fixations, but many of those fixations are cut short by a barrier crossing and become final fixations in the simulations. The longer the fixation, the more likely it is to cross a barrier, and so the average middle fixation duration is shorter in the simulations; this means that more fixations are required to achieve the same reaction times in our simulations as in the actual data.

Alternative Explanation for the Effects in Fig. 4 *A* and *B*. An alternative explanation for these trends is that subjects naturally fixate to the chosen item after their choice is made, and only then make a button press. This would mean that the effect seen in Fig. 4*A* is driven entirely by the final fixations. However, this alternative explanation is inconsistent with the results in Fig. 3 *A* and *B*, which rely directly on the logic of the model. In fact, under the model's assumption that there is nothing special about the final fixations, aside from the fact that they are interrupted by barrier crossings, the final fixation bias seen in Fig. 4*B* should have no effect on the trend seen in Fig. 4*A*.

SI Methods

Data Analysis. Every 20 ms, the eye tracker recorded whether the subject's fixation fell within one of the three items' ROIs, which were square boxes containing each item (an item fixation) or elsewhere on the screen (a nonitem fixation), or whether a fixation was not recorded (missing fixation). On average, subjects spent 84% of each choice trial within one of the items' ROIs, 12% of each choice trial looking elsewhere before the first item fixation, 4% of each choice trial looking elsewhere on the screen after the first item fixation, and <1% of each choice trial not looking at the screen. The average duration of the nonitem fixations was 28 ms with a median duration of 20 ms, i.e., one eye-tracker measurement. Therefore, these nonitem fixations were most likely due to momentary transitions between items or natural jitter in subjects' fixations near the edge of the ROIs.

Nonitem and missing fixation time before the first fixation was treated as nondecision time. Given the quality of the eye-tracking data after the first item fixations, we assume that these initial nonitem and missing fixations are simply due to peripheral attention processes involved in first fixation selection, and not part of the decision time. Both nonitem and missing fixations after the first fixation were treated as follows:

i) If the nonitem or missing fixations were recorded between fixations to the same item, then those blank fixations were changed to that item and assumed to be decision time. For example, a fixation pattern of "left, blank, left" would become "left, left, left."

ii) If the nonitem or missing fixations were recorded between fixations to different items, then those blank fixations were recorded as a nondecision time and discarded from further analysis.

Again, these gaps in the data are very short compared with the length of the trial, so that the specific way in which they are treated has a negligible impact on the reported results.

Simulated Fixation Patterns. Fixation locations for the first three fixations were determined according to Fig. S3, with the additional feature that the probabilities for the second fixation were increased/decreased by 4% for each positive/negative difference in the rankings of the items, based on the liking ratings. For example, suppose the subject first looks at the minimum ranked item, which happens to be on the left; the middle ranked item is in the center, and the maximum ranked item is on the right. The probability that the second fixation is to the center item is 29% + 4% = 33%, and likewise the probability for the right item is 71% − 4% = 67%. With the same three items, suppose instead that the subject first looks at the center item. Then the probability that the second fixation is to the left item is 60% – 8% = 52%, and likewise the probability for the right item is 40% + 8% = 48%. The probabilities for the third fixation were adjusted in exactly the same way, except with a 3% change per ranking, rather than 4%. The probabilities in Fig. S3 were estimated directly from the data by averaging across all trials, contingent on the identity of the previous fixation(s). The 3% and 4% adjustments were estimated by conditioning the second and third fixation location probabilities on both location and rank (best, middle, and worst). We found that location was the most important determinant of these fixation probabilities, but that rank had an average effect of 4% in the second fixation and 3% in the third fixation, averaged across all of the different contingencies.

Locations for fixations beyond the first three were determined according to Figs. S4 and S5. Fig. S4 shows the fixation probabilities once the subject has fixated on all three items at least once. Fig. S5 shows the fixation probabilities if the subject has not yet fixated on all three items in that trial. The probabilities in Fig. S5 were adjusted in exactly the same way as described above, with a 4% increase/decrease for each positive/negative difference in the rankings of the items. The probabilities in Figs. S4 and S5 were estimated from the fourth fixation data. For each distinct pattern of the first three fixations, we calculated the average probability that the fourth fixation was to one item or the other. We took these as approximations of the fixation probabilities for fixations $n > 3$.

It is also important to emphasize that imperfections in our characterization of the observed fixation process introduce noise into the simulation process, and thus can only reduce our ability to account for the data.

Goodness-of-Fit Calculations. For Figs. 2 *C* and *D* and 3*B* we could not compute χ^2 goodness-of-fit statistics because the dependent variables are not binary. R^2 statistics were also uninformative because of the high variability in average fixation duration from subject to subject. Instead we computed goodness of fits using the method from Krajbich et al. (1). There, we devised a different goodness-of-fit statistic, which works as follows: (*i*) For each value of the independent variable we "correct" the dependent variable by subtracting the average simulated value from each subject's average value. (*ii*) We then run a weighted least-squares (WLS) regression with the corrected dependent variable. The weights in the regression were equal to the inverse of the variance. Note that if the simulations fit the data well, the corrected data should be a flat line at zero. However, if the simulation fits poorly, then the WLS coefficient should be nonzero. So, for goodness of fits, we report the *P* values for the coefficients of these WLS regressions. If $P < 0.05$, we reject that the model fits the data.

Mixed-Effects Regressions. All mixed-effects regressions had random effects for subject-specific constants and slopes.

1. Krajbich I, Armel C, Rangel A (2010) Visual fixations and the computation and comparison of value in simple choice. *Nat Neurosci* 13:1292–1298.

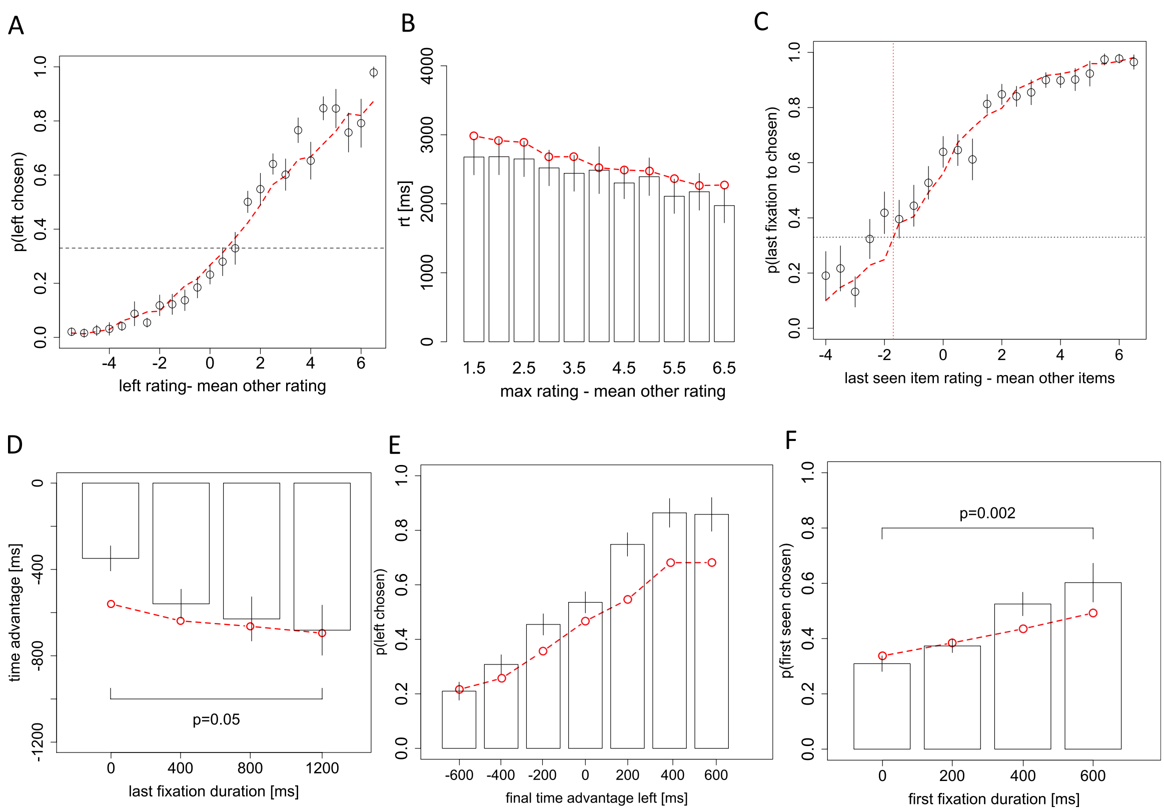

Fig. S1. Random fixation model. Same as (*A*) Fig. 2*A* (χ^2 goodness of fit, $P = 0.57$), (*B*) Fig. 2*C* (goodness-of-fit slope: $P = 0.75$, intercept: $P = 0.23$), (*C*) Fig. 3*A* (χ^2 goodness of fit, $P = 0.72$), (*D*) Fig. 3*B* (goodness-of-fit slope: $P = 0.053$, intercept: $P = 0.0003$), (*E*) Fig. 3*C* (χ^2 goodness of fit, $P = 0.014$), and (*F*) Fig. 3*E* (χ^2 goodness of fit, $P = 0.06$), but simulated with fixations that are drawn independently of value, after the first fixation.

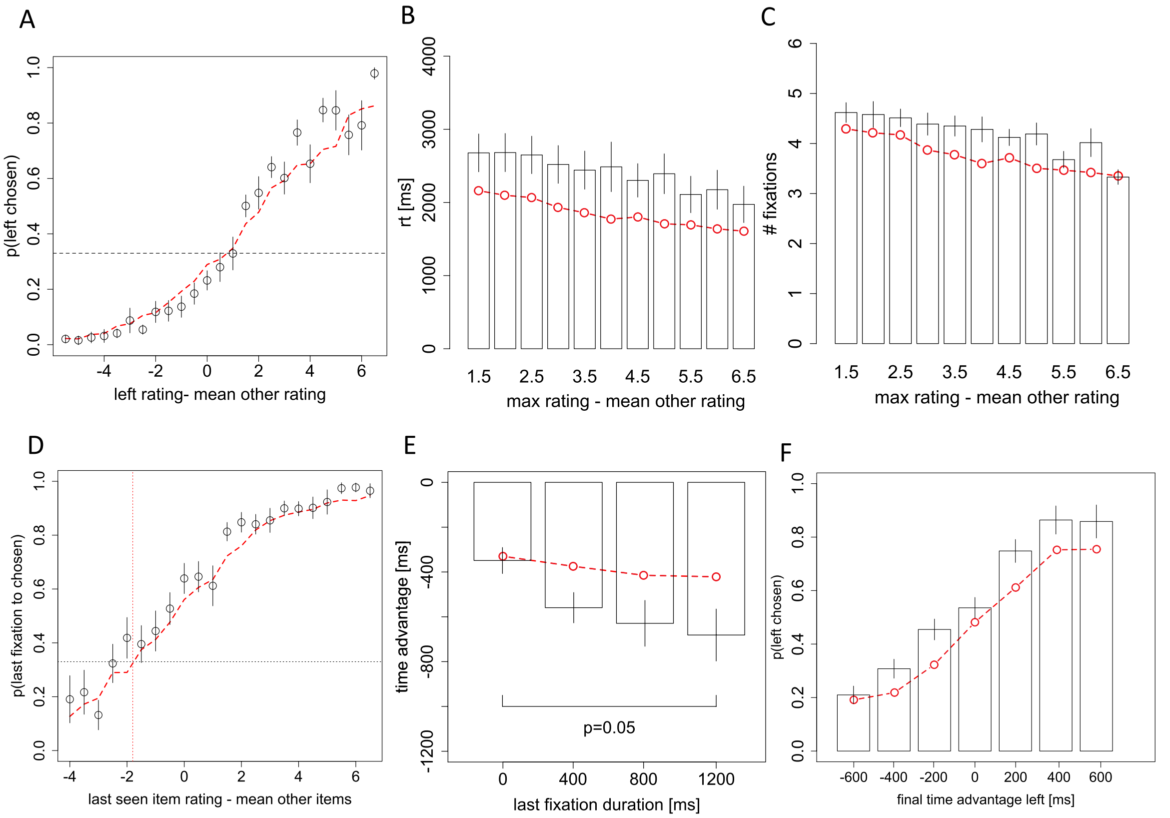

Fig. S2. Maximum vs. average model. Same as (*A*) Fig. 2*A* (χ^2 goodness of fit, $P = 0.36$), (*B*) Fig. 2*C* (goodness-of-fit slope: $P = 0.59$, intercept: $P = 0.002$), (*C*) Fig. 2*D* (goodness-of-fit slope: $P = 0.13$, intercept: $P = 0.0004$), (*D*) Fig. 3*A* (χ^2 goodness of fit, $P = 1$), (*E*) Fig. 3*B* (goodness-of-fit slope: $P = 0.023$, intercept: $P = 0.4$), and (*F*) Fig. 3*C* (χ^2 goodness of fit, $P = 0.37$), but simulated with the best vs. average model.

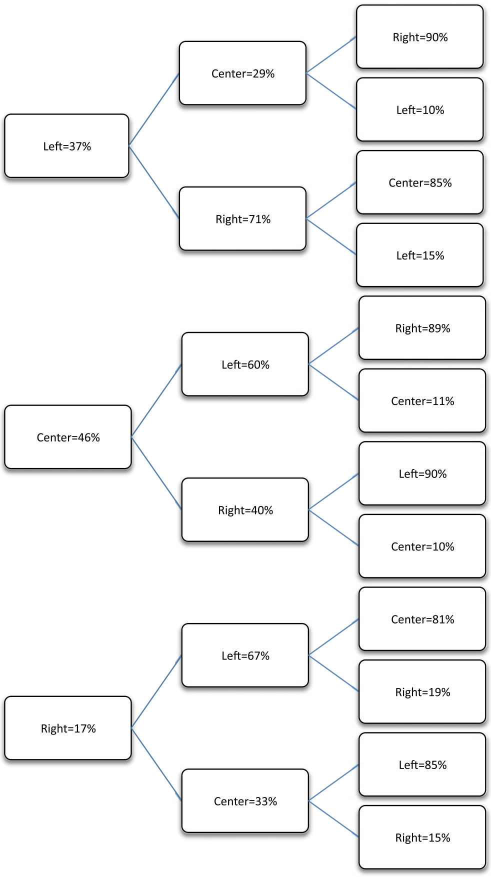

Fig. S3. Fixation probabilities for the first three fixations.

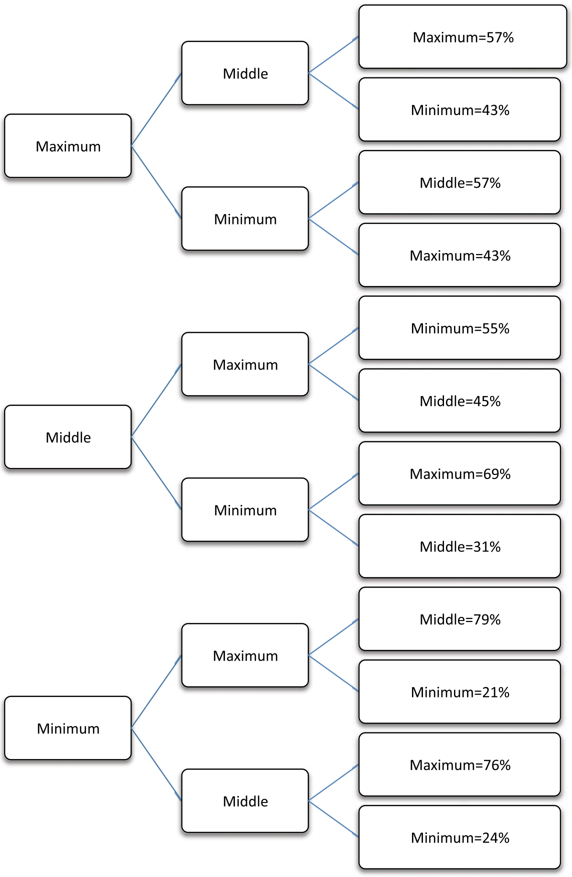

Fig. S4. Fixation probabilities after all three items have been seen.

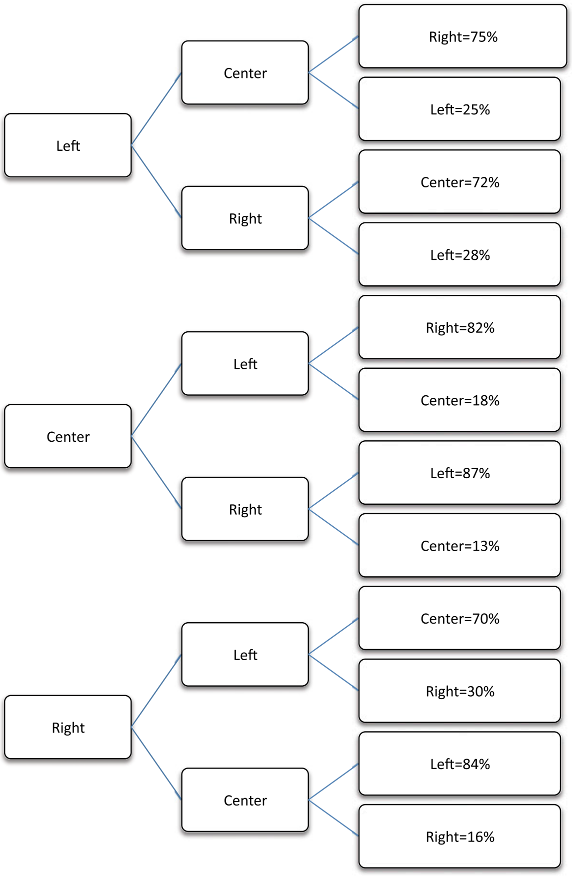

Fig. S5. Fixation probabilities before all three items have been seen.