Attention in Aversive Choice

Introduction

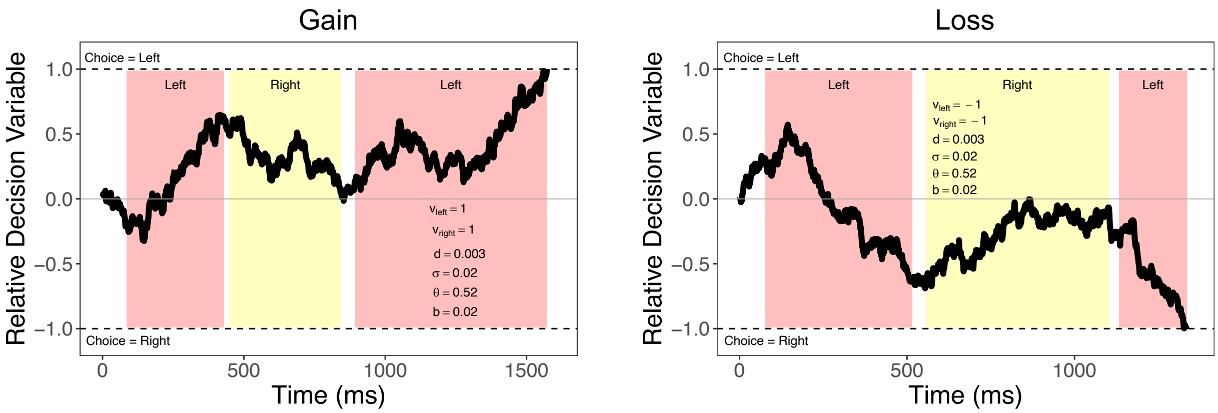


Fig. 1. aDDM Examples. (Gain Predictions) With positive value signals and an attentional parameter $\theta \in [0,1]$, the accumulator is biased towards the fixated option. (Loss Predictions) With negative value signals, the accumulator is instead predicted to be biased towards the non-fixated option. Colored vertical bands illustrate fixation locations.

- The aDDM predicts that attention in aversive choices should bias decisions away from more attended options.

Results

Paradigm

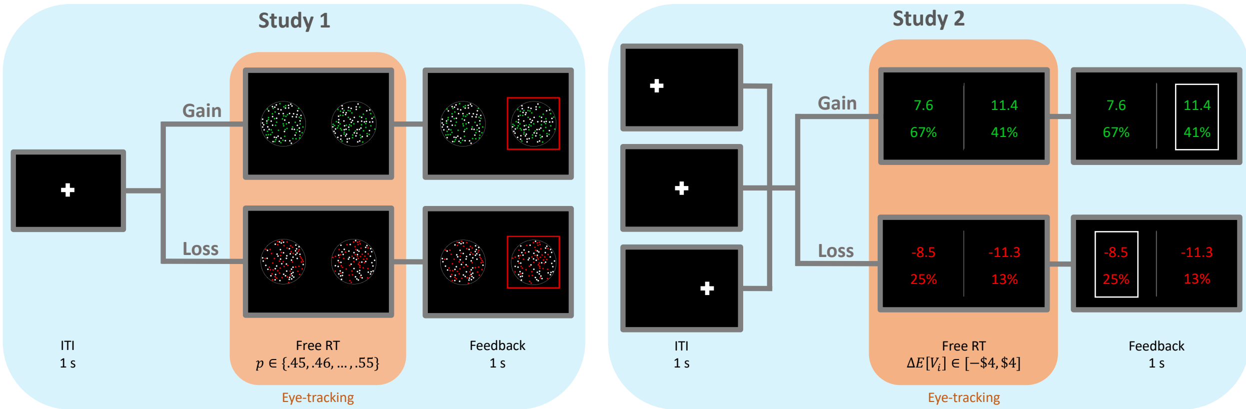


Fig. 2. Studies. Trials begin with a forced fixation cross for 1 s. In Study 1, the fixation cross is fixed in the center; but in Study 2, it varies evenly between the left, center, and right side of the screen. Participants then make a binary choice between two lotteries on the left and right side of the screen. In the gain condition, the lotteries have weakly positive outcomes. In the loss condition, they have weakly negative outcomes. As they make their choice, participants have free response times while we record the location of their gaze. After participants make a choice, feedback about the selected option is presented for 1 s. In Study 1, lotteries are presented as 100 dots in a grey circle. Green, white, and red dots represent the probability of gaining \$10, \$0, and -\$10, respectively. The number of green or red dots is drawn uniformly from $p \in \{45, \ldots, 55\}$, and the number of white dots is $100 - p$. In Study 2, the probabilities and outcomes for each lottery are presented in numerical format with an implicit 0 outcome. Differences in expected value are bounded between [-\$4, \$4], depending on condition.

- To test this hypothesis, we run two eye-tracking studies to investigate the role of attention in aversive choice.
- In Study 1, optimal information sampling could involve comparing colored and white dots, or it could involve simply counting green dots in the gain condition and white dots in the loss condition. Then inputs to the sequential sampling model are always positive. We run Study 2 to avoid ambiguity in the value signals.

Basic Psychometrics

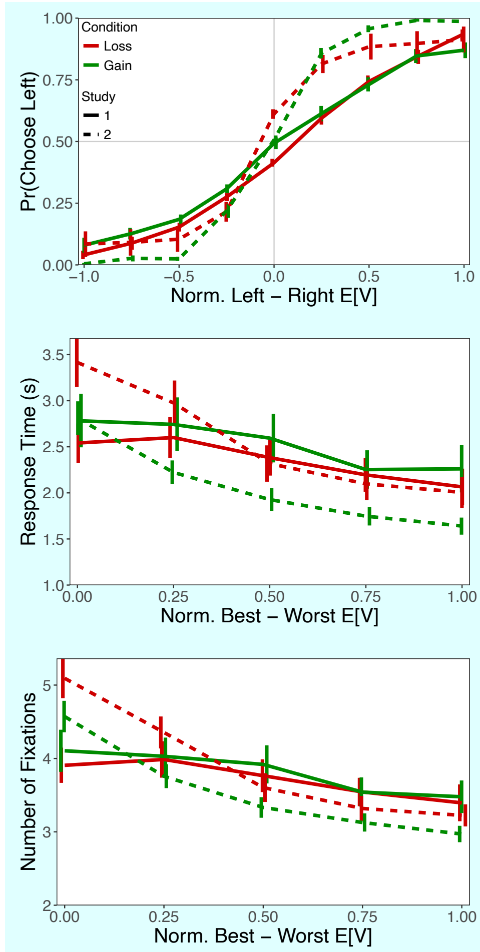


Fig. 3. Basic Psychometrics. The top row depicts the probability of choosing the left item as a function of the normalized expected value difference between the left and right lotteries (``relative value''). Expected values were normalized by dividing by the maximum magnitude of the difference. The middle row depicts response time as a function of normalized choice difficulty, measured by the expected value difference between the best and worst lottery then divided by the maximum magnitude of the difference. The bottom row depicts the number of fixations as a function of normalized choice difficulty. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

- In both studies, there were no meaningful differences in average choices or number of fixations across the two conditions.
- Response times were slightly slower in the loss condition in Study 2. We believe this is partially driven by self-reported difficulty in comprehending loss lotteries with implicit zero outcomes.
- See SFig. 1 for impact of attentional manipulations in Study 2 on basic psychometrics. Slight changes to average choices in gain condition, pretty much no impact on average choices in loss condition, or on response times.

- See S Table 1 for regressions associated with the figures.

Fixation Process

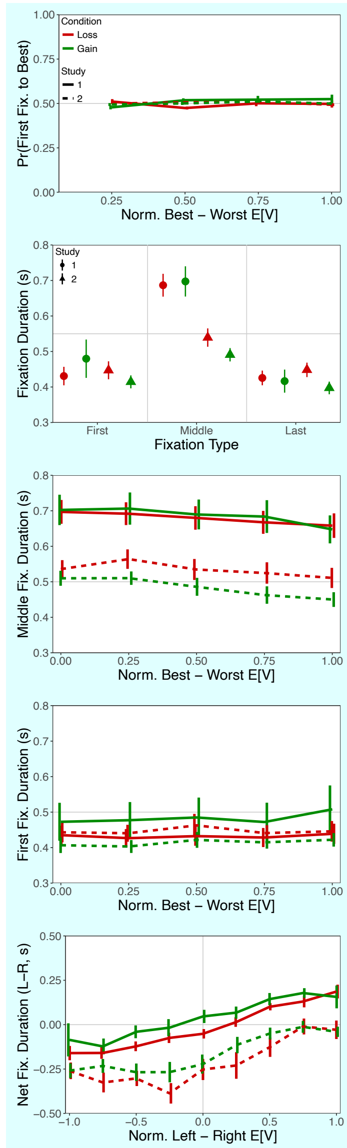


Fig. 4. Fixation Process. The first row depicts the probability of first fixating on the best lottery as a function of normalized choice difficulty. The best lottery is determined by expected value, ignoring risk preferences. The second row depicts fixation durations as a function of fixation type. The third row depicts middle fixation durations as a function of normalized choice difficulty. The fourth row depicts first fixation durations as a function of normalized choice difficulty. The fifth row depicts net fixation duration to the left lottery as a function of its normalized relative expected value. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

- No significant differences across conditions in first fixation to best, middle fixation durations, or first fixation durations.

- In Row 2, fixations durations were significantly longer in loss condition, but differences are small.
- In Row 5, we see participants spend increasingly more time looking at the option they favor more. In Study 2, we see the right-side lottery receives more attention on average. See SFig. 2 for an explanation: participants most frequently utilize 2 fixations when the fixation cross starts left, whereas they most frequently utilize 3 fixations when the fixation cross starts right. This is not explained by Bayesian models of attention allocation.
- See SFig. 3.for impact of attentional manipulations on Fixation Process in Study 2. Slightly longer first fixation durations when fixation cross left or right compared to center. Net fixation durations favor left more, the closer the fixation cross gets to the left side.
- See S Table 2 for regressions associated with the figure, and S Table 3 for regressions associated with SFig. 2, Additional Fixation Properties.

Attentional Choice Biases

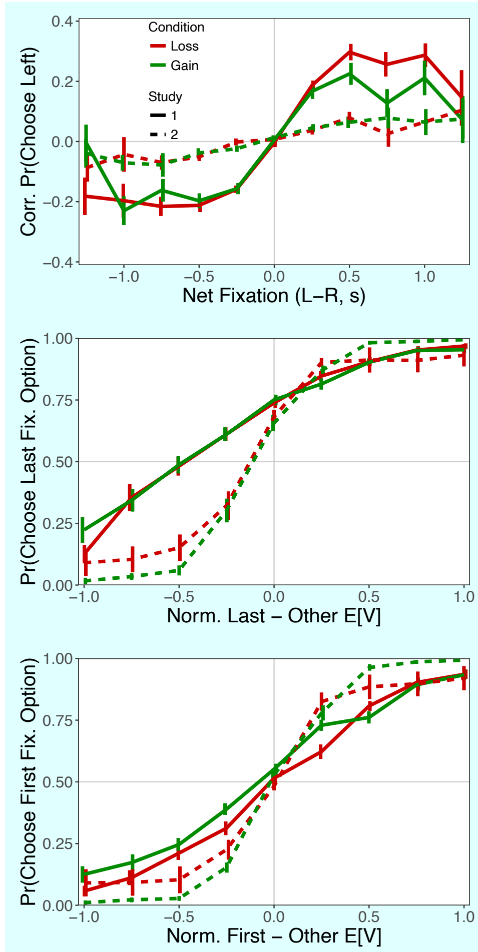


Fig. 5. Attentional Choice Biases. The top row depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. The corrected probability is computed by subtracting from each choice observation (1=left, 0=right) the proportion of which left is chosen at each relative value. The middle row depicts the probability of choosing the last fixated lottery as a function of the normalized relative expected value of the last fixated lottery. The bottom row depicts the probability of choosing the first fixated lottery as a function of the normalized relative expected value of the first fixated lottery. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

- **Unlike the predictions of the aDDM, attentional choice biases did not experience a reversal in the loss condition. In fact, for both studies, they are nearly identical in both conditions.**
- Row 3: no evidence of first fixation location bias.
- See SFig. 4 for effect of attentional manipulations on attentional choice biases. Not much impact on net or last fixation bias. It does impose a small first fixation location bias.
- See S Table 4 for regressions associated with the figure.

Model Selection

- SFig. 5 shows that the standard aDDM with $\theta \in [0,1]$ cannot explain the lack of attentional choice bias reversals in losses. While the aDDM with $\theta \in (0,2)$ can predict the behavior in our data, it does not make intuitive sense. Two other models can explain our data. The AddDDM is another model of attention that postulates that attention plays a value-independent role in the sequential sampling process. We are also proposing the RaDDM, which incorporates reference-dependent value signals into the aDDM. The RaDDM with a reference point rule that selects reference points close to the minimum outcome in a context is capable of predicting our data.

Table 1. Model Comparison Regression Tests in the Loss Condition

		Exploratory			Confirmatory		Joint	
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE	Est.	SE
Study 1	β_0 Intercept	0.35	0.15	*				
log(RT)	β_1 Abs. Net Value	-0.21	0.03	*				
(Linear)	β_2 Overall Value	-0.04	0.01	*				
Study 2	β_0 Intercept	0.76	0.11	*				
log(RT)	β_1 Abs. Net Value	-0.13	0.01	*				
(Linear)	β_2 Overall Value	-0.03	0.01	*				

* indicates significance at the 95% confidence level. "Abs." = Absolute.

- The relationship between response times and overall value, emphasized in Smith and Krajbich (2019), provides a test for what model our participants might be using.
- S Table 5 shows that the RT(OV) test is capable of distinguishing between data simulated using the aDDM, AddDDM, and RaDDM in the loss condition. RTs are increasing in overall value with the aDDM, independent with the AddDDM, and decreasing with the RaDDM.
- Table 1 shows the results of the RT(OV) test applied to data from both of our studies. **The tests reveal a small but significantly negative relationship between RT and OV in the loss condition for both studies. This suggests that people are using some form of reference-dependent value signals during evidence accumulation.**
- S Table 6 replicates the results from Smith and Krajbich (2019) in the Study 1 gain condition. We do not see it replicated in the Study 2 gain condition.

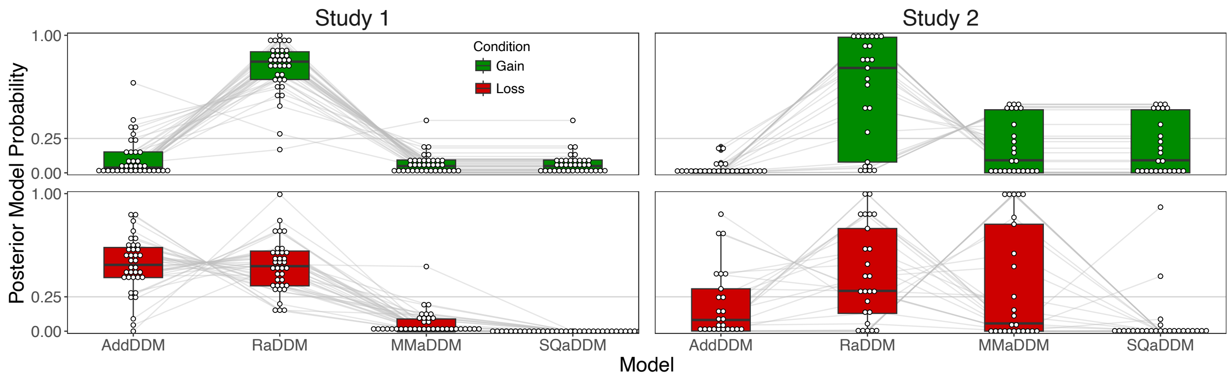


Fig. 6. Model Comparison. Each plot depicts the posterior model probabilities within a study and condition. Each dot represents the posterior model probability for a model (x-axis) for a single participant. For each participant, the sum of their four dots spread across the three columns in each plot adds to 1. Boxplots present the 25th, 50th, and 75th percentiles. AddDDM: the additive model of attention. RaDDM: the reference-dependent aDDM with standard $[0,1]$ bounds on the attentional parameter. MMaDDM: the standard aDDM with MaxMin Prospect Theory value signals. SQaDDM: the standard aDDM with Status Quo Prospect Theory value signals.

- We simultaneously fit 4 models using the aDDM Toolbox by Enkavi et al. (2024). This allows us to, for each participant, calculate posterior model probabilities of each model. The 4 models we selected were the AddDDM, RaDDM, MMaDDM, and SQaDDM. We selected the MMaDDM and SQaDDM based on Baillon et al. (2020) in order to compare the RaDDM against some formal reference point rules.
- The MMaDDM and SQaDDM require that Prospect Theory is fitted to participants' choice data before feeding in the predicted value signals into the aDDM. SFig. 6 shows the fitted Prospect Theory parameters for both reference point rules, as well as, the out-of-sample choice performance of the two rules. Note that both rules are capable of explaining choices well and yield similar Prospect Theory estimates.
- We did not design our studies to distinguish between these models. Therefore, the MMaDDM and SQaDDM are identical in the gain condition of both studies, resulting in identical posterior model probabilities.
- In the Study 1 gain condition, the RaDDM clearly outperforms the other models for most subjects. In the Study 1 loss condition, both the AddDDM and RaDDM perform well. Participants who are best fit by the AddDDM are worse fit by the RaDDM (and vice versa), suggesting that there might be subgroups of participants with different roles of attention during their decision-making process.
- In the Study 2 gain condition, the RaDDM performs the best for most subjects, though the MMaDDM and SQaDDM also perform well for some participants. For all the subjects who are not fit well by the RaDDM, they are fit well by the MMaDDM and SQaDDM. In the Study 2 loss condition, the RaDDM and MMaDDM perform well. Again, for those who were not fit well by the RaDDM, most were fit very well by the MMaDDM.

- Due to the consistency in its performance along with the results from the RT(OV) test, we will be basing model analyses on the RaDDM.
- See SFig. 7 for Alluvial plots depicting how frequently participants had matching best-fitting models in the gain and loss conditions.
- See SFIg. 8 for model recovery analyses. These exercises show that the data generating process can be recovered with the method used above.

Reference-Dependent aDDM (RaDDM)

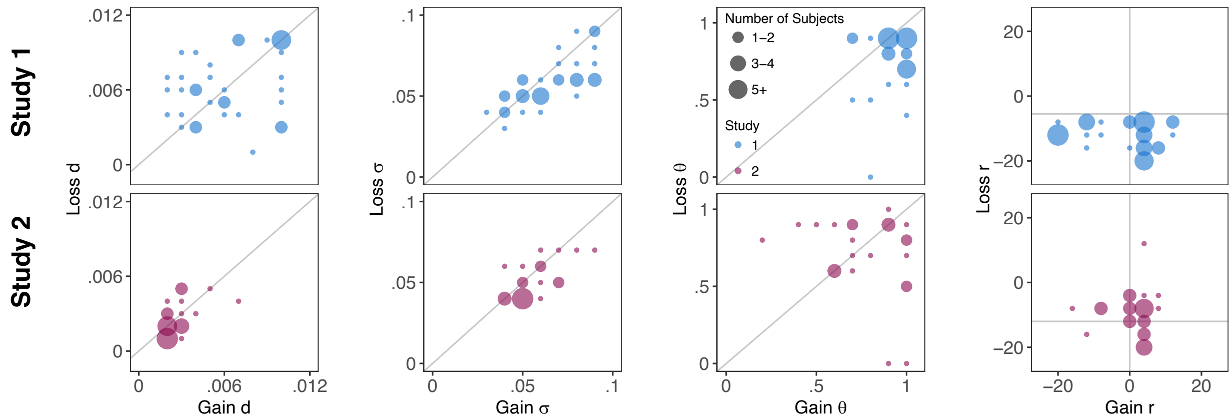
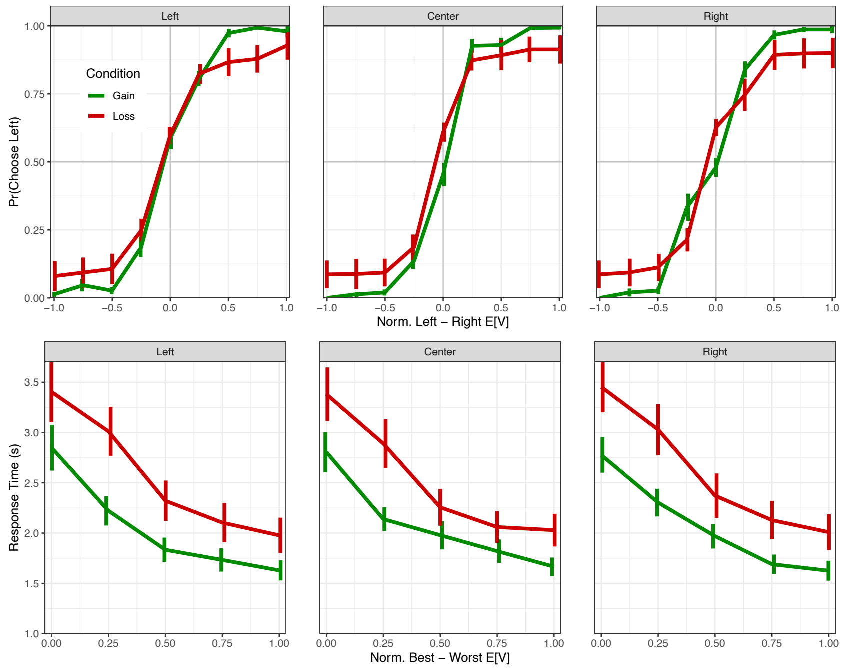


Fig. 7. Participant-Level RaDDM Estimates. Estimates of the drift rate (d), noise (σ), attentional bias (θ), and reference point (r) in the loss condition as a function of their counterpart in the gain condition. For d, σ, and θ, grey lines indicate the equality across the two conditions. For r, grey lines indicate the minimum possible outcome in that condition for that study.

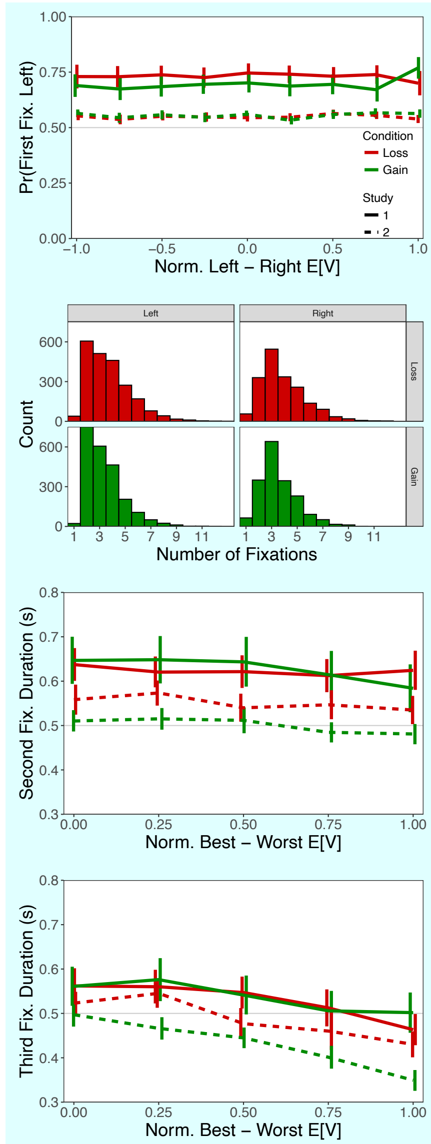
- Drift rates differ between the two studies, mostly due to differences in the magnitudes of the value signals. Drift rate does not seem to differ in a meaningful way across conditions in either study.
- Noise does not seem to differ in a meaningful way across conditions in either study.
- The attentional bias parameter does not seem to differ much across conditions in Study 2, which is consistent with the nearly identical attentional choice biases we observed in Fig. 5. In Study 1, the attentional bias parameter does shrink slightly, which is inconsistent with Fig. 5.
- Overall, attentional bias parameters are much closer to 1 than in previous studies. This is due to the magnitude of the value signals, which are now with respect to a reference point. These value signals are significantly larger in magnitude than those seen in previous studies. Therefore, even slight deviations from 1 in the attentional bias parameter can impose much larger changes in the accumulator compared to other studies. This can be seen by the negative correlation between the reference point and attentional bias parameter in SFig. 9 (except in the Study 2 loss condition).
- Due to computational constraints, we test free reference points in the range $[-20, 12]$ in step sizes of 4. Free reference points in the gain condition of Study 1 most often fall at around 4. This is close to the minimum expected value in this context. In the Study 1 loss condition, the free reference point always falls below the minimum possible outcome of -5.5. In both conditions for Study 2, the free reference point is typically estimated near the minimum possible outcome in that context.
- **These results suggest that many participants may be using the minimum possible outcome in a context as the reference point for evaluating lottery outcomes. This implies that participants are accumulating evidence over positive reference-dependent value signals, even when dealing with aversive choices.**

- SFig. 10 shows the result of parameter recovery exercises with the RaDDM. Drift rate, attentional bias, and reference point are typically recovered well. Sometimes when data generating noise is too small, the model dramatically overestimates the noise parameter.
- SFig. 11 shows the out-of-sample predictions of the RaDDM. The model is trained on all trials that are not divisible by ten, then those estimated parameters are used to generate predictions about behavior in the trials that are divisible by ten. The model is able to capture the average quality of choices, response times, net fixation bias, and last fixation bias, though it struggles to accurately predict response times in Study 2 when value differences are small.

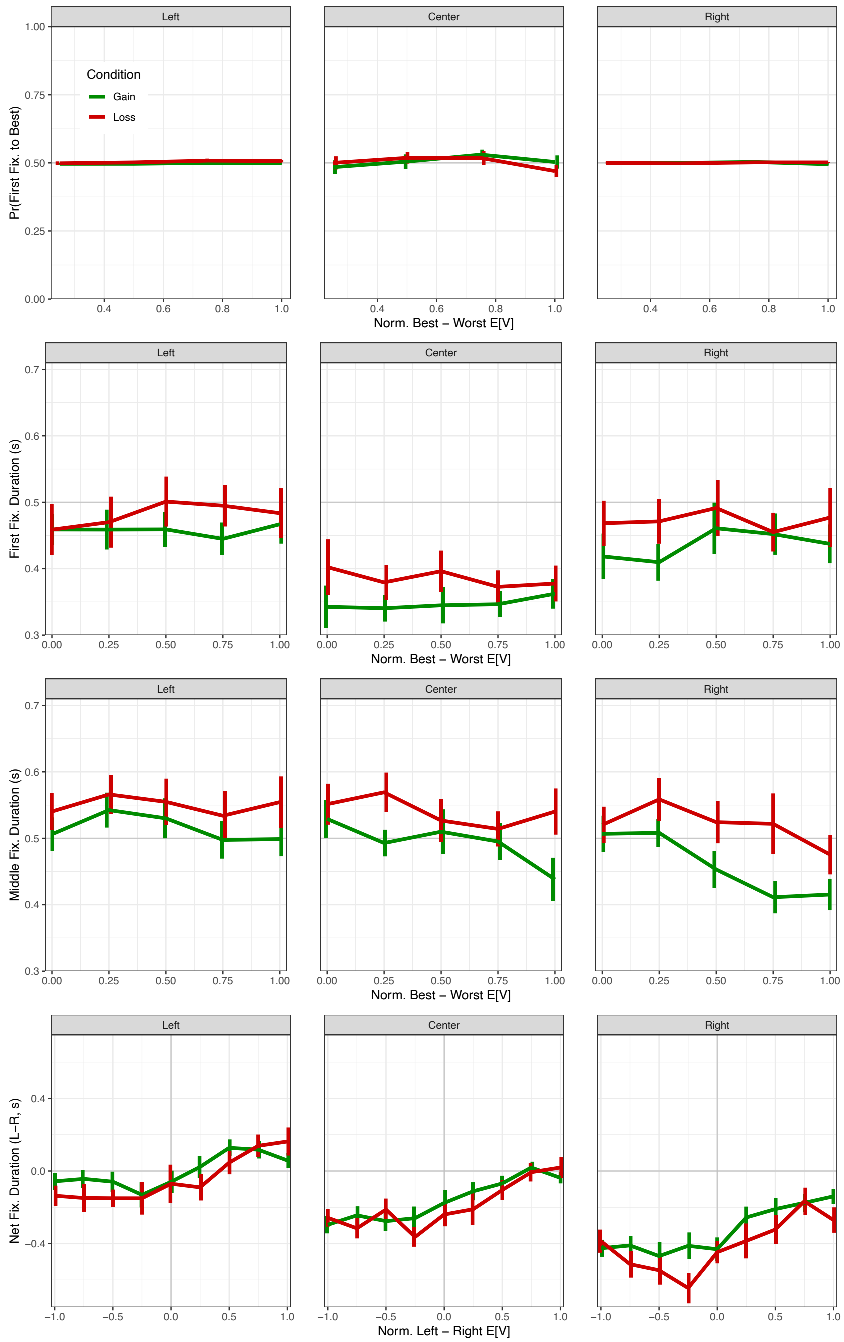
Supplementary Figures



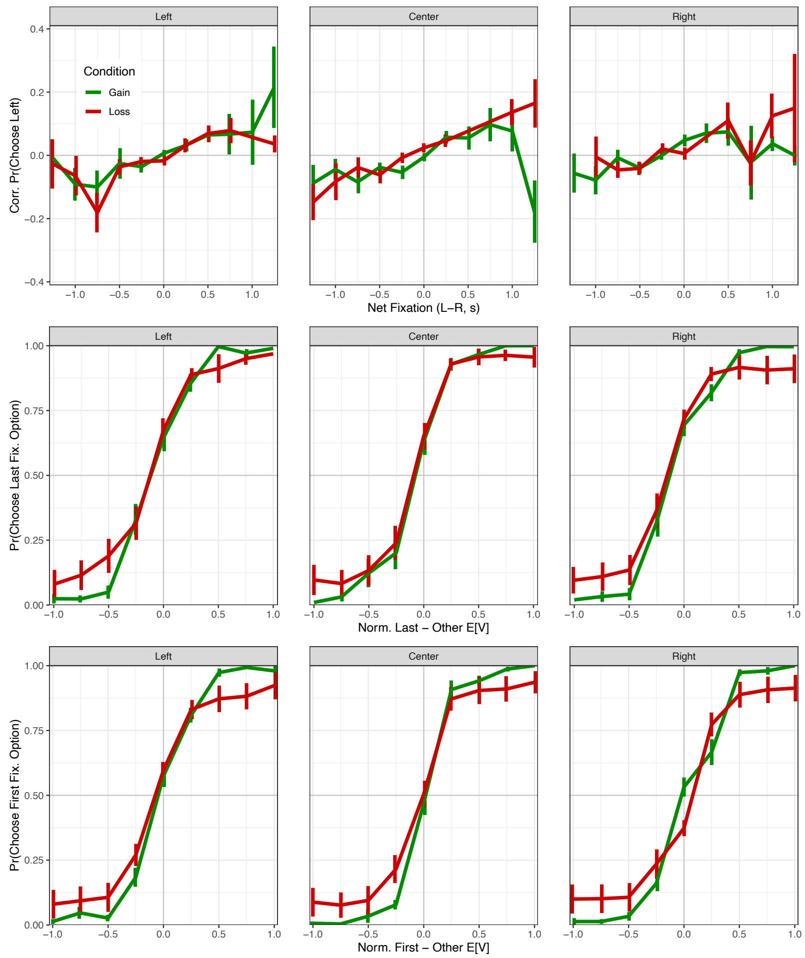
SFig. 1. Basic Psychometrics with Attentional Manipulations. The top row depicts the probability of choosing the left lottery as a function of the normalized expected value difference between the left and right lottery. Value differences are normalized by the maximum possible value difference. The bottom row depicts response times as a function of the normalized choice difficulty. Choice difficulty is measured by the difference between the best and worst expected value and is normalized by the maximum possible choice difficulty. Columns denote the location of the fixation cross which manipulates the location of first fixation. Error bars denote standard error of the mean across participants.



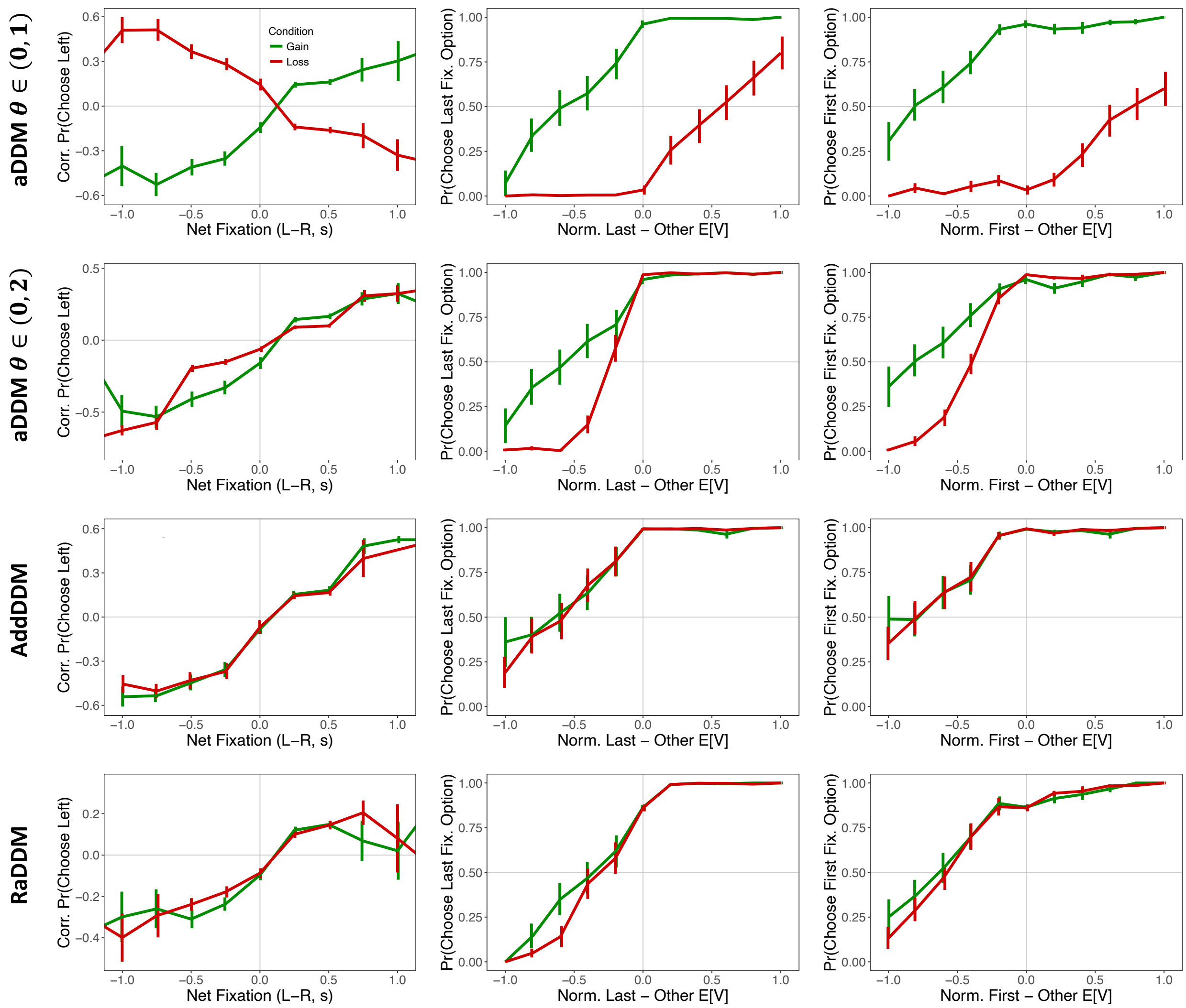
SFig. 2. Additional Fixation Properties. The first row depicts the probability of first fixating left as a function of choice difficulty. The second row depicts histograms of the pooled number of fixations in a trial, separately by condition and the location of first fixation, for Study 2 only. The third row depicts the second fixation duration as a function of the normalized relative value. The fourth row depicts the third fixation duration as a function of the normalized relative value.



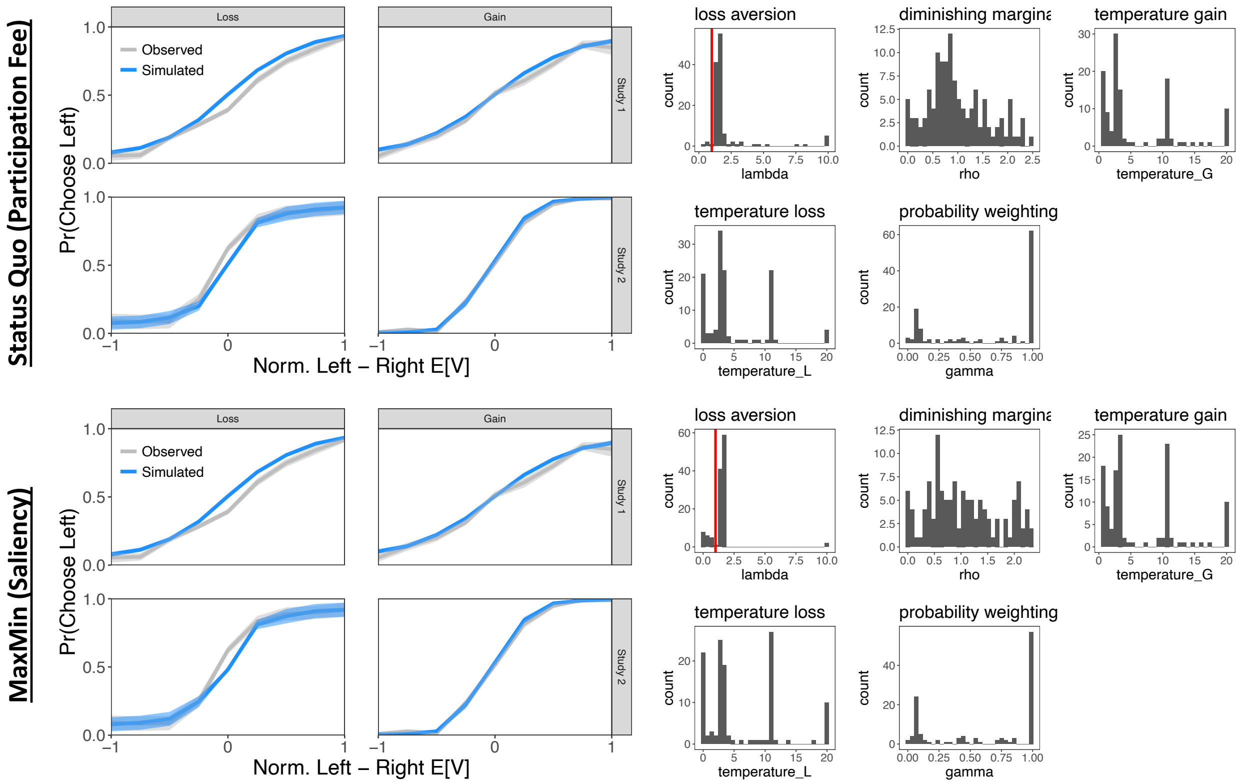
SFig. 3. Fixation Process with Attentional Manipulations. The first row depicts the probability of first fixating on the best lottery as a function of normalized choice difficulty. The second row depicts the first fixation durations as a function of normalized choice difficulty. The third row depicts average middle fixation durations as a function of normalized choice difficulty. The fourth row depicts the net fixation duration to the left lottery as a function of the normalized expected value difference. Columns denote the location of the fixation cross which manipulates the location of first fixation. Error bars denote standard error of the mean across participants.



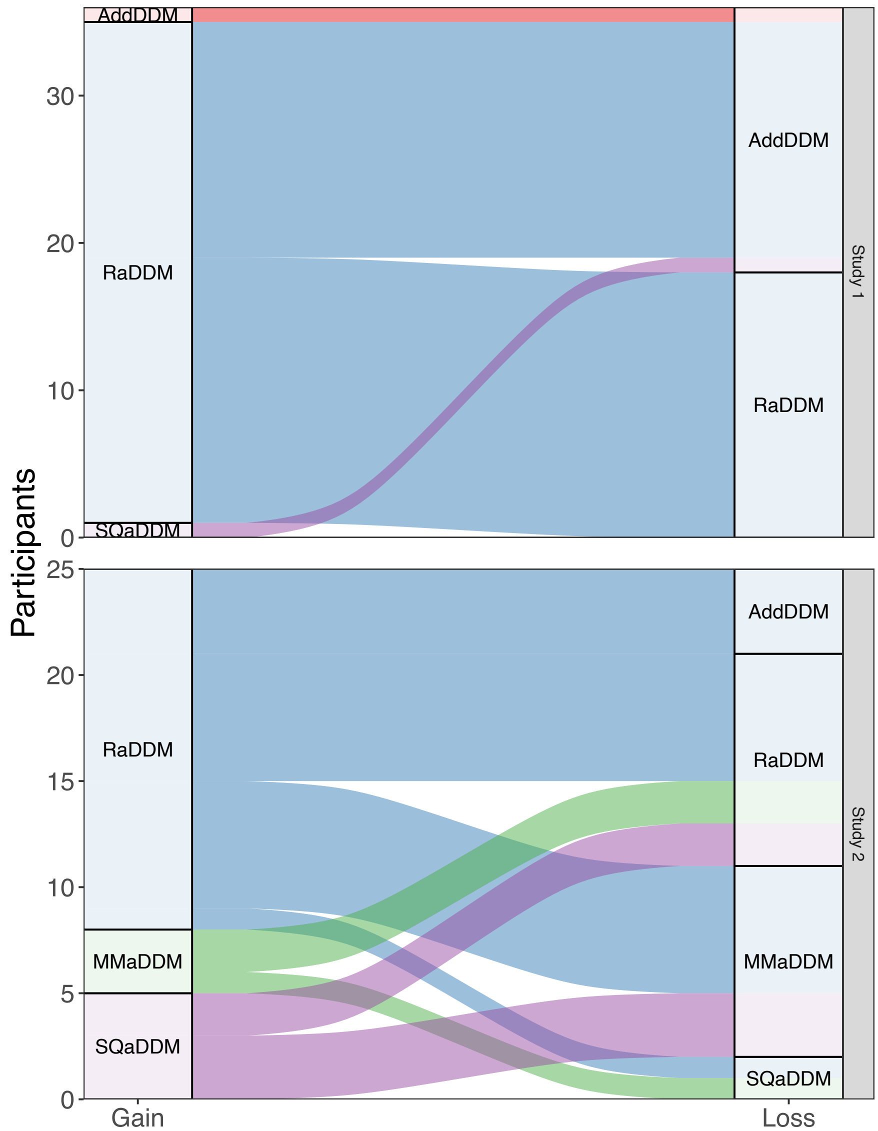
SFig. 4. Attentional Choice Biases with Attentional Manipulations. The top row depicts the corrected probability of choosing the left lottery as a function of the net fixation time to the left lottery. Corrected probabilities are calculated by taking the choice observation (1=left, 0=right) and subtracting the proportion of times left was chosen at each value difference. The middle row depicts the probability of choosing the last fixated option as a function of the normalized relative expected value of the last fixated lottery. The bottom row depicts the probability of choosing the first fixated option as a function of the normalized relative expected value of the first fixated lottery. Columns denote the location of the fixation cross which manipulates the location of first fixation. Error bars denote standard error of the mean across participants.



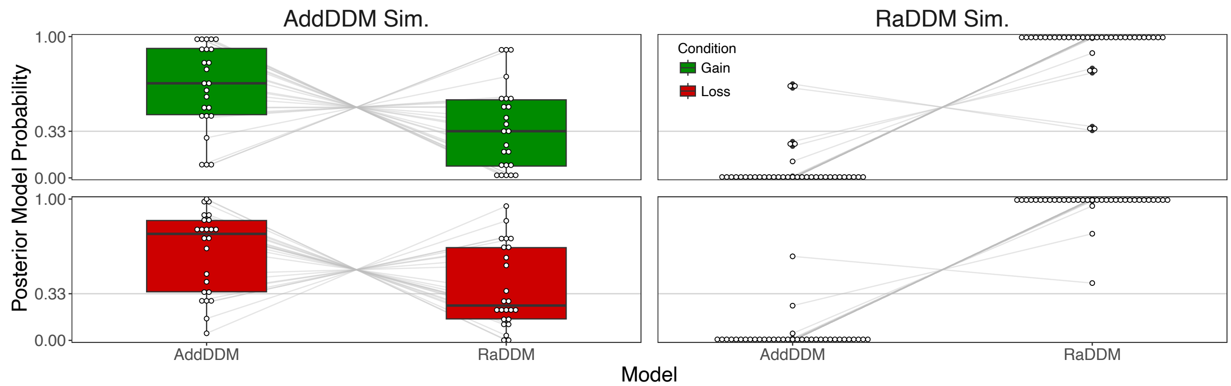
SFig. 5. Simulations of Attentional Choice Biases. For each model and condition, we generated a simulated dataset of 200 trials for each of 25 simulated subjects, each with their own random draw of parameter values. Columns depict attentional choice biases as seen in Fig. 5: (Left) Corrected probability of choosing the left option as a function of net fixation to the left option. (Middle) Probability of choosing the last fixated option as a function of normalized net value of the last fixated option. (Right) Probability of choosing the first fixated option as a function of normalized net value of the first fixated option. (First Row) aDDM simulations of attentional choice biases using $\theta \in (0,1)$ in both conditions. (Second Row) aDDM simulations using $\theta \in (0,1)$ in the gain condition and $\theta \in (1,2)$ in the loss condition. (Third Row) AddDDM simulations using $\eta \in [0.0001, 0.02]$. (Fourth Row) RaDDM simulations using $\theta \in (0,1)$. Drift rate, noise, and bias parameters, as well as, fixation properties were drawn from distributions similar to those found by Eum et al. (2023). Error bars denote the standard error of the mean across simulated subjects.



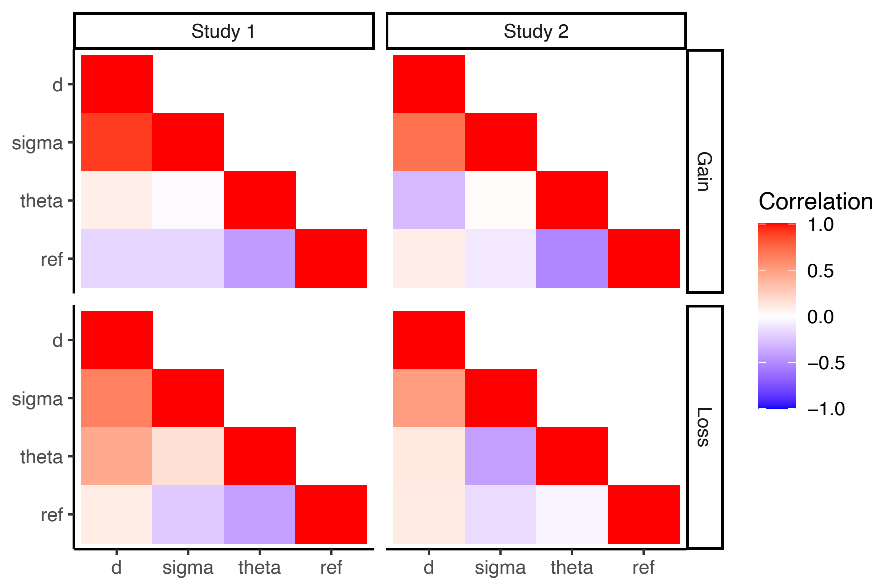
SFig. 6. Out-of-Sample Predictions and Estimates of Prospect Theory Models. Prior to fitting the MMaDDM or SQaDDM, we fit the choice data to Prosepct Theory using the MaxMin or Status Quo reference point rules. (Left Columns) We plot the probability of choosing the left lottery as a function of the normalized expected value difference between left and right lotteries. (Right Columns) Histograms of the parameter estimates. We estimated Prospect Theory with 5 parameters using MLE: loss aversion, diminishing marginal returns, temperature in the gain and in the loss conditions, and Prelec probability reweighting. The red vertical line in the loss aversion plots indicates the minimum value of λ for which losses are aversive.



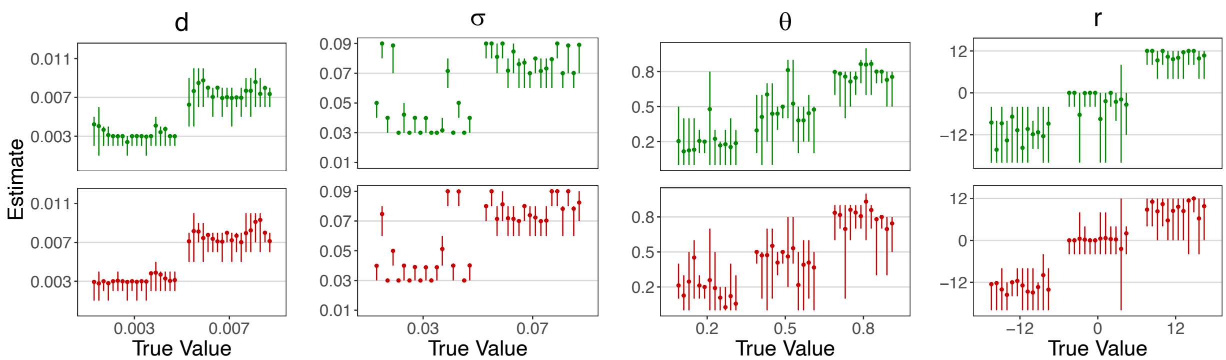
SFig. 7. Best-Fitting Model For Each Participant Across Conditions. On the left, we plot the best fitting model for each participant in the gain condition. On the right, we plot the best fitting model for each participant in the loss condition. Colored lines connect the boxes from left to right, indicating for each participant whether the best fitting model in the gain condition is the same, or different, in the loss condition. Rows denote which study the participants belong to.



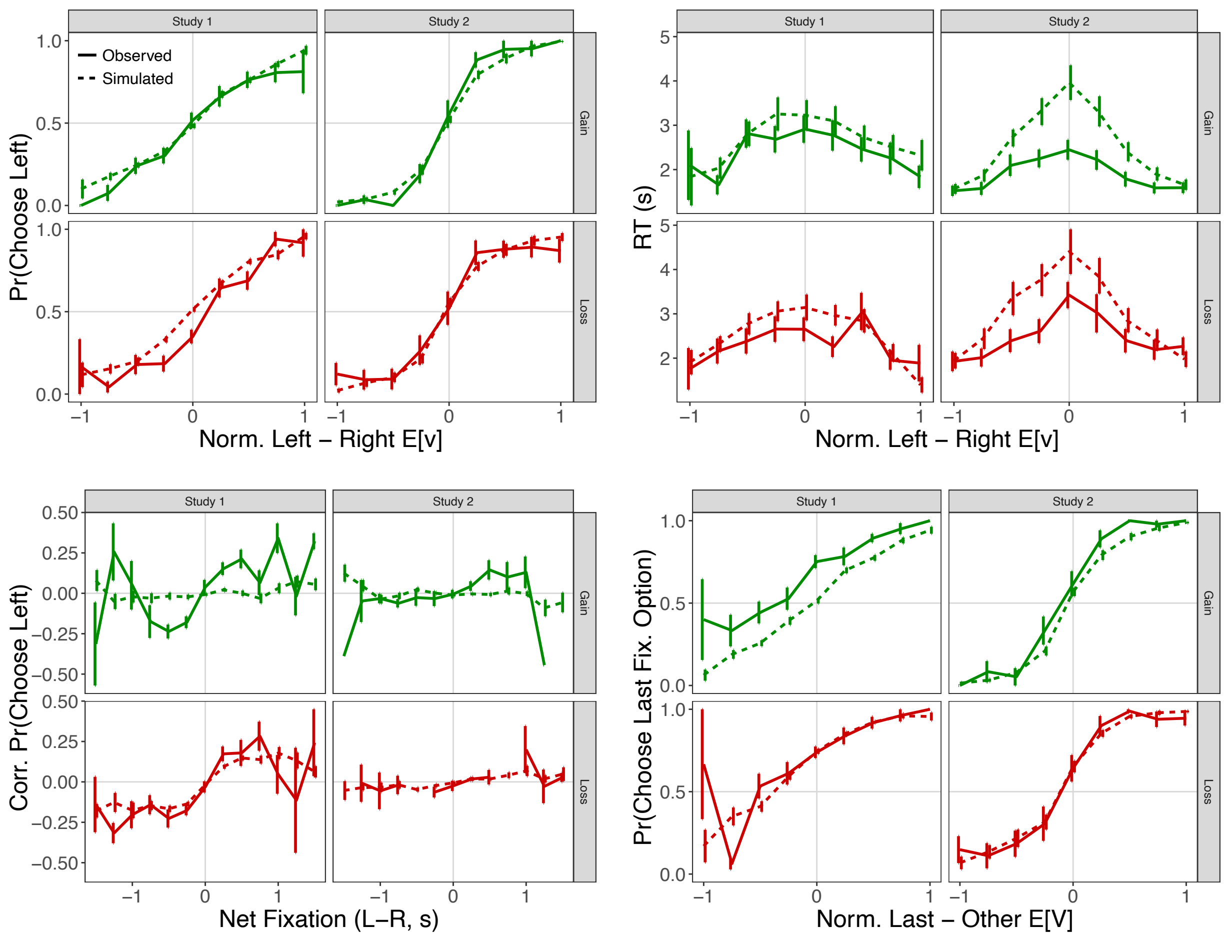
SFig. 8. Model Recovery Exercises. For each column, we use one of the models to simulate multiple datasets with different parameter combinations. We then simultaneously fit the simulated data with both models and compare posterior model probabilities. (Left) We simulate 24 datasets for each combination of AddDDM parameters: $d \in \{.003, .007\}$, $\sigma \in \{.03, .07\}$, $\eta \in \{.001, .003, .005, .007, .009, .011\}$. (Right) We simulate 36 datasets for each combination of RaDDM parameters: $d \in \{.003, .007\}$, $\sigma \in \{.03, .07\}, \theta \in \{.1, .5, .9\}, r \in \{-12, 0, 12\}$. Rows are separated based on condition. Boxplots depict the 25th, 50th, and 75th percentiles.



SFig. 9. RaDDM Parameter Correlations. Correlation matrices for parameter estimates across participants. Rows separate by condition, columns separate by study.



SFig. 10. RaDDM Parameter Recovery. For each of the 36 simulations, we calculate discrete marginal posterior distributions for each parameter. We compare the mean and approximate 95% HDI of each marginal posterior with its data generating (``true'') value. Approximate 95% HDIs were calculated using the discrete values just outside of the mass containing 95% of the density; in other words, they are ≥95% HDIs.



SFig. 11. RaDDM Out-of-Sample Predictions. (Top Left) The probability of choosing left as a function of the normalized relative expected value of the left option, as in Row 1 of Fig. 3. (Top Right) Response time as a function of the normalized best minus worst expected value, as in Row 2 of Fig. 3. (Bottom Left) Corrected probability of choosing the left option as a function of the net fixation time to the left option, as in Row 1 of Fig. 5. The corrected probability is computed by subtracting from each choice observation (coded as 1 if left chosen, and 0 otherwise) the proportion with which left is chosen at each relative expected value. (Bottom Right) The probability of choosing the last fixated option as a function of the normalized net expected value of the left option, as in Row 2 of Fig. 5. Rows separate the data by condition, and columns separate by study. Out-of-sample data consists of all trials divisible by 10 from all participants. 10 simulated datasets per participant. Error bars represent the standard error of the mean across all simulations for all participants.

Supplementary Tables

*don’t worry, confirmatory and joint values are just placeholders.

Supplementary Table 1. Regressions associated with the basic psychometric results in Fig. 3.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
Study 1										
Left Chosen	Intercept	-0.17	0.12		-0.17	0.12		-0.17	0.12	
(Logistic)	N. Left - Right E[V]	2.65	0.13	*	2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	-0.16	0.11		-0.16	0.11		-0.16	0.11	
	Interaction	0.35	0.17	*	0.35	0.17	*	0.35	0.17	*
RT (s)	Intercept	2.83	0.30	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.62	0.15	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	-0.22	0.24		-0.16	0.11		-0.16	0.11	
	Interaction	0.14	0.14		0.35	0.17	*	0.35	0.17	*
# of Fix.	Intercept	4.16	0.28	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.66	0.13	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	-0.16	0.17		-0.16	0.11		-0.16	0.11	
	Interaction	0.16	0.13		0.35	0.17	*	0.35	0.17	*
Study 2										
Left Chosen	Intercept	0.13	0.07		-0.17	0.12		-0.17	0.12	
(Logistic)	N. Left - Right E[V]	7.05	0.56	*	2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	0.08	0.09		-0.16	0.11		-0.16	0.11	
	Interaction	-0.57	0.86		0.35	0.17	*	0.35	0.17	*
RT (s)	Intercept	2.56	0.17	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-1.02	0.13	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	0.70	0.17	*	-0.16	0.11		-0.16	0.11	
	Interaction	-0.39	0.11	*	0.35	0.17	*	0.35	0.17	*
# of Fix.	Intercept	4.21	0.20	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-1.39	0.16	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	0.57	0.16	*	-0.16	0.11		-0.16	0.11	
	Interaction	-0.39	0.12	*	0.35	0.17	*	0.35	0.17	*

“N.” = Normalized.

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

Supplementary Table 2. Regressions associated with the fixation process results in Fig. 4.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
Study 1										
1st Fix. Best	Intercept	-0.10	0.06		-0.17	0.12		-0.17	0.12	
(Logistic)	N. Best - Worst E[V]	0.22	0.12		2.65	0.13	*	2.65	0.13	*
(Row 1)	Loss Condition	0.12	0.09		-0.16	0.11		-0.16	0.11	
	Interaction	-0.33	0.17		0.35	0.17	*	0.35	0.17	*
Mid. Fix. Dur.	Intercept	0.72	0.05	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.05	0.02	*	2.65	0.13	*	2.65	0.13	*
(Row 3)	Loss Condition	-0.01	0.04		-0.16	0.11		-0.16	0.11	
	Interaction	0.01	0.02		0.35	0.17	*	0.35	0.17	*
1st Fix. Dur.	Intercept	0.47	0.05	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	0.02	0.01		2.65	0.13	*	2.65	0.13	*
(Row 4)	Loss Condition	-0.04	0.04		-0.16	0.11		-0.16	0.11	
	Interaction	-0.03	0.02		0.35	0.17	*	0.35	0.17	*
Net Fix. Dur.	Intercept	0.04	0.03		-0.17	0.12		-0.17	0.12	
(Linear)	N. Left - Right E[V]	0.18	0.02	*	2.65	0.13	*	2.65	0.13	*
(Row 5)	Loss Condition	-0.06	0.03	*	-0.16	0.11		-0.16	0.11	
	Interaction	0.02	0.03		0.35	0.17	*	0.35	0.17	*
Study 2										
1st Fix. Best	Intercept	-0.02	0.08		-0.17	0.12		-0.17	0.12	
(Logistic)	N. Best - Worst E[V]	0.04	0.12		2.65	0.13	*	2.65	0.13	*
(Row 1)	Loss Condition	0.05	0.12		-0.16	0.11		-0.16	0.11	
	Interaction	-0.07	0.17		0.35	0.17	*	0.35	0.17	*
Mid. Fix. Dur.	Intercept	0.52	0.02	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.06	0.02	*	2.65	0.13	*	2.65	0.13	*
(Row 3)	Loss Condition	0.04	0.02		-0.16	0.11		-0.16	0.11	
	Interaction	0.03	0.02		0.35	0.17	*	0.35	0.17	*
1st Fix. Dur.	Intercept	0.40	0.02	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	0.02	0.01		2.65	0.13	*	2.65	0.13	*
(Row 4)	Loss Condition	0.04	0.02	*	-0.16	0.11		-0.16	0.11	
	Interaction	-0.02	0.02		0.35	0.17	*	0.35	0.17	*
Net Fix. Dur.	Intercept	-0.16	0.04	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Left - Right E[V]	0.14	0.02	*	2.65	0.13	*	2.65	0.13	*
(Row 5)	Loss Condition	-0.05	0.03		-0.16	0.11		-0.16	0.11	
	Interaction	0.02	0.04		0.35	0.17	*	0.35	0.17	*

"N." = Normalized.

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

Supplementary Table 3. Regressions associated with the additional fixation properties in Fig. S4.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
		Study 1								
1st Fix. L	Intercept	1.20	0.30	*	-0.17	0.12		-0.17	0.12	
(Logistic)	N. Left - Right E[V]	0.06	0.09		2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	0.34	0.15	*	-0.16	0.11		-0.16	0.11	
	Interaction	-0.11	0.11		0.35	0.17	*	0.35	0.17	*
2nd Fix. Dur.	Intercept	0.66	0.06	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.05	0.01	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	-0.02	0.04		-0.16	0.11		-0.16	0.11	
	Interaction	0.02	0.02		0.35	0.17	*	0.35	0.17	*
3rd Fix. Dur.	Intercept	0.58	0.05	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.09	0.02	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	-0.01	0.04		-0.16	0.11		-0.16	0.11	
	Interaction	0.01	0.03		0.35	0.17	*	0.35	0.17	*
		Study 2								
1st Fix. L	Intercept	0.22	0.07	*	-0.17	0.12		-0.17	0.12	
(Logistic)	N. Left - Right E[V]	0.01	0.05		2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	-0.03	0.05		-0.16	0.11		-0.16	0.11	
	Interaction	-0.01	0.07		0.35	0.17	*	0.35	0.17	*
2nd Fix. Dur.	Intercept	0.52	0.03	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.04	0.02	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	0.05	0.02		-0.16	0.11		-0.16	0.11	
	Interaction	0.01	0.03		0.35	0.17	*	0.35	0.17	*
3rd Fix. Dur.	Intercept	0.51	0.03	*	-0.17	0.12		-0.17	0.12	
(Linear)	N. Best - Worst E[V]	-0.15	0.02	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	0.04	0.03		-0.16	0.11		-0.16	0.11	
	Interaction	0.03	0.03		0.35	0.17	*	0.35	0.17	*

"N." = Normalized.

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

Supplementary Table 4. Regressions associated with the attentional choice bias results in Fig. 5.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
Study 1										
Corr. L Chosen	Intercept	0.01	0.01		-0.17	0.12		-0.17	0.12	
(Linear)	Net Fix. Left	0.36	0.06	*	2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	0.00	0.01		-0.16	0.11		-0.16	0.11	
	Interaction	0.02	0.05		0.35	0.17	*	0.35	0.17	*
Last Fix. Chosen	Intercept	1.25	0.18	*	-0.17	0.12		-0.17	0.12	
(Logistic)	N. Last - Other E[V]	2.54	0.15	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	0.06	0.08		-0.16	0.11		-0.16	0.11	
	Interaction	0.27	0.20		0.35	0.17	*	0.35	0.17	*
1st Fix. Chosen	Intercept	0.18	0.10		-0.17	0.12		-0.17	0.12	
(Logistic)	N. 1st - Other E[V]	2.61	0.14	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	-0.39	0.11	*	-0.16	0.11		-0.16	0.11	
	Interaction	0.36	0.16	*	0.35	0.17	*	0.35	0.17	*
Study 2										
Corr. L Chosen	Intercept	0.01	0.00		-0.17	0.12		-0.17	0.12	
(Linear)	Net Fix. Left	0.09	0.02	*	2.65	0.13	*	2.65	0.13	*
(Top)	Loss Condition	-0.00	0.01		-0.16	0.11		-0.16	0.11	
	Interaction	0.01	0.02		0.35	0.17	*	0.35	0.17	*
Last Fix. Chosen	Intercept	0.58	0.14	*	-0.17	0.12		-0.17	0.12	
(Logistic)	N. Last - Other E[V]	7.04	0.59	*	2.65	0.13	*	2.65	0.13	*
(Middle)	Loss Condition	0.13	0.13		-0.16	0.11		-0.16	0.11	
	Interaction	-0.67	0.82		0.35	0.17	*	0.35	0.17	*
1st Fix. Chosen	Intercept	-0.03	0.06		-0.17	0.12		-0.17	0.12	
(Logistic)	N. 1st - Other E[V]	7.02	0.56	*	2.65	0.13	*	2.65	0.13	*
(Bottom)	Loss Condition	0.08	0.09		-0.16	0.11		-0.16	0.11	
	Interaction	-0.59	0.83		0.35	0.17	*	0.35	0.17	*

"Corr." = Corrected. "L" = Left. "N." = Normalized.
* indicates significance in all data sets at the 95% confidence level.
* indicates a significant effect that was not present in all three data sets.

Supplementary Table 5. Regression tests for model comparison on simulated loss condition data from each model.

Dept. Var.	Indept. Var.	Est.	SE	
log(RT)	β_0 Intercept	0.04	0.14	
aDDM Sim.	β_1 Abs. Net Value	-0.27	0.04	*
(Linear)	β_2 Overall Value	0.08	0.01	*
log(RT)	β_0 Intercept	-1.17	0.14	*
AddDDM Sim.	β_1 Abs. Net Value	-0.09	0.04	*
(Linear)	β_2 Overall Value	0.00	0.00	
log(RT)	β_0 Intercept	-0.56	0.26	*
RaDDM Sim.	β_1 Abs. Net Value	-0.50	0.06	*
(Linear)	β_2 Overall Value	-0.17	0.02	*

* indicates significance at the 95% confidence level.
"Abs." = Absolute. "Sim." = Simulations.

We simulated data for the Study 2 loss condition using the aDDM with $\theta \in (0,1)$, the AddDDM, and the RaDDM. 200 trials for 25 simulated subjects with parameters and fixation properties similar to Eum et al. (2023). We then use Eq. 1 to run the same regression test used in Table **??**. These results confirm that the relationship between response time and overall value can be used to distinguish the models in our data: (Top) the aDDM predicts a positive β_2, (Middle) the AddDDM predicts an insignificant β_2, and (3) the RaDDM predicts a negative β_2.

Supplementary Table 6. Replication: Response time is decreasing in overall value in gain condition.

		Exploratory			Confirmatory		Joint	
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE	Est.	SE
Study 1	β_0 Intercept	1.20	0.16	*				
$log(RT_{Gain})$	β_1 Abs. Net Value	-0.23	0.03	*				
(Linear)	β_2 Overall Value	-0.05	0.01	*				
Study 2	β_0 Intercept	0.84	0.07	*				
$log(RT_{Gain})$	β_1 Abs. Net Value	-0.11	0.01	*				
(Linear)	β_2 Overall Value	-0.01	0.00					

* indicates significance at the 95% confidence level. "Abs." = Absolute.