Attention and range-normalized sequential integration in aversive value-based choices

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August 11, 2026

Abstract

Attentional biases reliably shape simple choices between desirable options, pulling decisions toward the option that receives more visual attention. Prominent process models of attention and choice make a sharp prediction about what should happen when every option is undesirable: because these models discount the value of the unattended option, and because discounting a negative value makes it more attractive, attentional choice biases should reverse. Across two eye-tracking experiments involving risky choices between gains or losses, we find no reversal. Participants were more likely to choose the option they fixated longer and the option they last fixated, and the magnitude of both biases was indistinguishable across gains and losses. This rules out any account in which attention acts multiplicatively on unnormalized, signed value, including the standard Attentional Drift–Diffusion Model. Using a nesting framework over surviving accounts, we find that the data are best explained by evidence accumulation over range-normalized value signals. Our results indicate that unavoidable losses are evaluated relative to a contextual reference point near the worst available outcome, rendering subjective values weakly positive and preserving the attentional mechanisms that govern choices among gains.

Keywords— decision making, attention, fixations, simple choice, losses, neuroeconomics

Introduction

In our daily lives, decisions between desirable options ("appetitive choices"), such as choosing a meal or a product, often involve attentional biases that skew choices toward the option receiving more attention (S. M. Smith & Krajbich, 2018; Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Tavares, Perona, & Rangel, 2017; Krajbich, 2019). However, we also frequently encounter decisions in which all outcomes are undesirable and we must select the lesser of two evils ("aversive choices"). For example, individuals may be forced to decide which bill to prioritize under a limited budget or which unpleasant medical procedure to endure. In such aversive choices, it is unclear whether attention continues to nudge decisions in the direction of the attended option. The central goal of this paper is to establish a clear relationship between choices, response times, and fixation patterns in aversive decision-making, and to use that relationship to discipline models of how attention enters the choice process.

Previous work has shown that manipulating attention in favor of an option biases choices toward that option (Tavares et al., 2017; Bhatnagar & Orquin, 2022), and that this effect can reverse in aversive choices when options are presented sequentially under fixed response times (Armel, Beaumel, & Rangel, 2008). However, the use of a sequential presentation paradigm may have altered the underlying choice process in ways that promote attentional bias reversals. Sequential presentation encourages separate evaluations of options and discourages direct comparison, which is more likely to induce attentional bias reversals than environments that allow free viewing (Eum, Dolbier, & Rangel, 2023; Basu & Savani, 2017, 2019). Moreover, decision-makers may have reached a decision prior to the fixed response time, in which case subsequent processes could have confounded observed behavior by the time a response was required (Resulaj, Kiani, Wolpert, & Shadlen, 2009).

Despite these concerns, the attentional choice biases reported by Armel et al. (2008) are consistent with a prominent model of attention and decision-making: the Attentional Drift–Diffusion Model (aDDM). The aDDM and its extensions provide a framework for investigating the role of attention in the decision process while accounting for factors such as decision noise and response caution (Krajbich et al., 2010; S. M. Smith & Krajbich, 2018). A key feature of the aDDM is an attentional parameter that yields a quantitative measure of how attention influences evidence accumulation. In studies of appetitive choice, estimates of this parameter suggest that individuals discount the value of the non-fixated option during comparison (Krajbich et al., 2010; Krajbich & Rangel, 2011; S. M. Smith & Krajbich, 2018, 2019; Tavares et al., 2017; Eum et al., 2023). However, in aversive choices, because a discounted negative value is greater than its original value, applying the same attentional discounting mechanism would make the non-fixated option appear *better* than it actually is (i.e. its value becomes closer to 0). Therefore, we hypothesized that in simple aversive choices, attention to an option would bias choices toward the *unattended* option (see Fig. 1). Behaviorally, this implies that decision-makers would be (a) less likely to choose the option they attended to longer and (b) less likely to choose the option they last fixated on.

To test these hypotheses, we conducted two studies involving simple risky choices. In both studies, participants made a series of binary choices between two lotteries, organized into blocks based on two conditions: (a) a *Gain condition*, in which all lotteries had weakly positive outcomes, and (b) a *Loss condition*, in which all lotteries had weakly negative outcomes. In Study 1, lotteries were represented visually using 100 colored dots arranged inside a circle to convey probabilities over fixed outcomes, whereas Study 2 presented lottery information numerically.

Prior research has examined the role of attention in risky choice, largely focusing on settings with strictly positive outcomes. These studies consistently find that the lottery that receives more attention is more likely to be chosen (Fiedler & Glöckner, 2012; S. M. Smith & Krajbich, 2018;

Stewart, Hermens, & Matthews, 2016; Alsharawy, Zhang, Ball, & Smith, 2021). This is consistent with the predictions of the aDDM. Koop and Johnson (2013) even showed that as participants attended to attributes within a gamble, their mouse trajectories moved toward that gamble, which the authors interpreted as reflecting their latent choice process. Evidence from the loss domain is sparser and less consistent. Sheng et al. (2020) coupled eye-tracking with a diffusion model in mixed gambles and found preferential gaze toward the loss attribute, which indexed a valuation bias rather than a response bias. The most closely related evidence on attention in aversive choices comes from Brandstätter and Körner (2014), who used a multi-attribute decision paradigm and found a bias toward both the more frequently fixated lottery and the last-fixated lottery, even when the last-fixated outcome was negative. These findings run counter to the predictions of the standard aDDM and to other work on attention in multi-attribute choices involving both appetitive and aversive attributes (Fisher, 2021, 2017; Yang & Krajbich, 2023). More broadly, the causal status of attention in choice remains actively contested (Mormann & Russo, 2021; Bhatnagar & Orquin, 2022). In light of these mixed results, an additional goal of this paper is to clarify the role of attention in risky aversive choices using both behavioral analyses and sequential sampling models to shed light on decision processes involving exclusively aversive outcomes.

To preview our results, behavior in aversive choices does *not* align with the predictions of the standard aDDM. Participants remain biased toward the option they attend to more, and toward the option they fixate last, just as in appetitive choices, and the magnitude of these biases is statistically indistinguishable across domains. We treat this null as the primary contribution, because it is constraining. Any admissible model of attention in choice must preserve attentional pull toward the attended option when every option value is negative, and this requirement eliminates an entire class of accounts: those in which attention acts multiplicatively on unnormalized, signed value. There are a few alternative frameworks that are consistent with this finding. Either attention must influence accumulation in a way that does not depend on the sign of value, or the value signal entering the comparison process must itself be sign-invariant. To adjudicate between these possibilities, and to allow for the possibility that both operate, we develop a nesting framework we call the Hybrid Attentional Drift–Diffusion Model (Hybrid aDDM), which spans the standard aDDM, additive attention models, range-normalized variants, and their combination. Formal model comparison, out-of-sample simulation, and an independent behavioral signature all point to the same conclusion: value signals are range-normalized prior to accumulation, and attention contributes through both a value-dependent and a value-independent channel.

Results

Overview of Experimental Design and Analysis

Task. Participants completed two eye-tracking experiments involving binary risky choices between lotteries in either a Gain or a Loss condition (see Fig. 2). In both conditions, participants chose between two lotteries presented simultaneously under free viewing and free response time, allowing for direct comparison between options. In the Gain condition, all lottery outcomes were weakly positive, whereas in the Loss condition all outcomes were weakly negative. Study 1 used perceptual lottery representations based on dot arrays that conveyed probabilities over fixed outcomes, while Study 2 presented lottery information numerically to rule out strategy switching across conditions. Across both studies, lottery sets were constructed to avoid stochastic dominance and to tightly control the range of expected values, ensuring comparable choice difficulty across Gain and Loss conditions. In Study 2, the initial fixation location was experimentally manipulated to examine

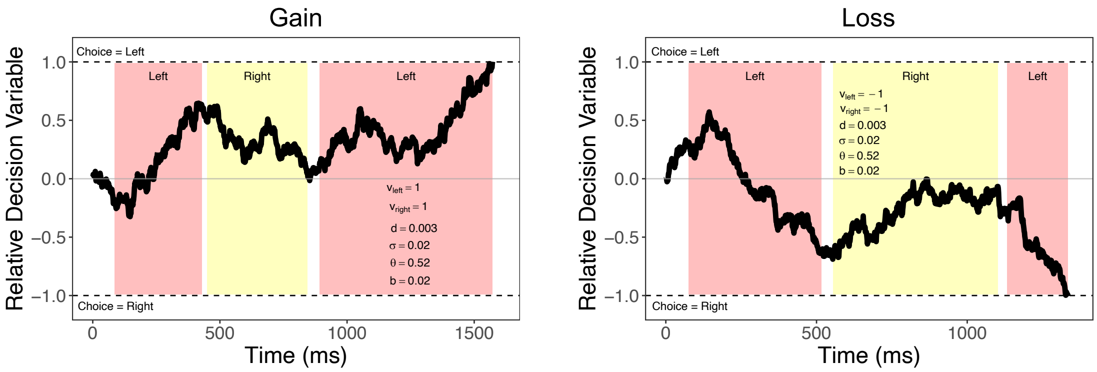

Fig. 1. Standard aDDM Examples. (Gain) With positive value signals and an attentional discounting parameter in $(0, 1)$, the accumulator is biased towards the fixated option. (Loss) With negative value signals, the standard aDDM accumulator is biased towards the nonfixated option. Colored vertical bands illustrate fixation locations.

how early attentional allocation influenced subsequent fixation patterns and choice behavior.

Participants were recruited from the local community and completed several hundred trials each. A subset of trials served as sanity checks with clearly dominant options, allowing us to identify and exclude inattentive participants. Eye movements were recorded throughout the decision period, enabling fine-grained measurement of fixation location, duration, and sequence. Fixations were classified to the left option, right option, or outside the option regions, and brief gaps due to blinking or tracker noise were handled using standard recoding procedures. For more details, see *Methods*.

Inference Strategy. Since our central claim is the absence of a predicted effect, guarding against both overfitting and undisciplined post-hoc analysis is essential. We adopted a split-sample inference strategy (see Fig. 3). For each study, data were divided into exploratory and confirmatory samples collected under identical protocols. Analyses, model specifications, and hypothesis tests were developed using the exploratory data and then evaluated in the confirmatory data, which was not examined until the analysis plan was fixed. We report both samples separately throughout, so that every result in this paper can be read as an internal replication. When results were consistent across samples, we also report estimates from the pooled (joint) dataset.

For computational modeling, trials were further divided into training and out-of-sample subsets based on trial number. Models were fit exclusively on the training data, and their predictions were evaluated on held-out trials to assess out-of-sample performance. Behavioral analyses throughout the paper rely on mixed-effects regressions to account for repeated observations within participants, and statistical tests are reported separately for Gain and Loss conditions to isolate differences in decision processes across domains.

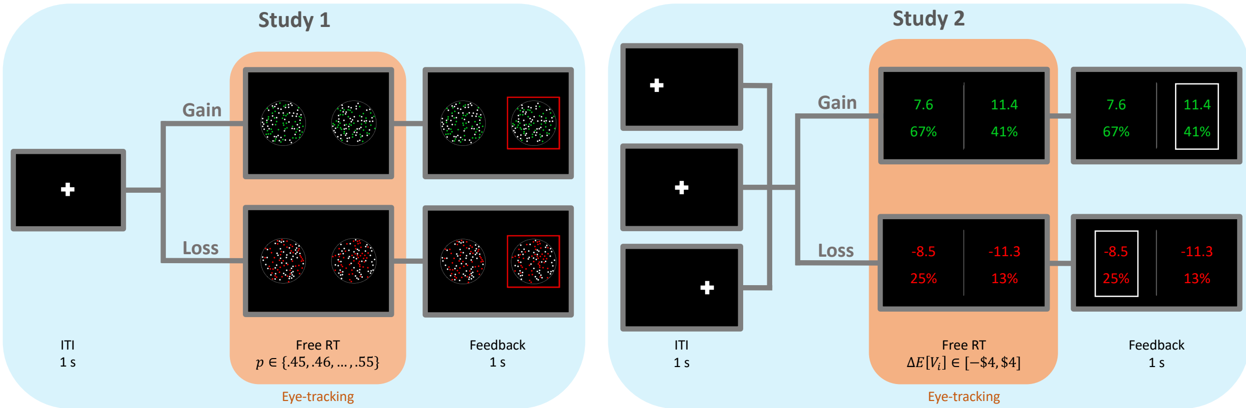

Fig. 2. Tasks. Trials begin with a forced fixation cross for 1 s. In Study 1, the fixation cross is fixed in the center; but in Study 2, it varies evenly between the left, center, and right side of the screen. Participants then make a binary choice between two lotteries on the left and right. In the Gain condition, the lotteries have weakly positive outcomes. In the Loss condition, they have weakly negative outcomes. During this phase, participants have free response time as we record the location of their gaze. After the choice, feedback about the chosen option is presented for 1 s. In Study 1, each lottery is presented as 100 dots in a grey circle. Green dots represent the probability of gaining \$10, white dots represent the probability of \$0, and red dots represent the probability of -\$10. 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, information about each lottery is presented in numerical format, with differences in expected value ($\Delta E[V_i]$) bounded between $[-\$4, \$4]$.

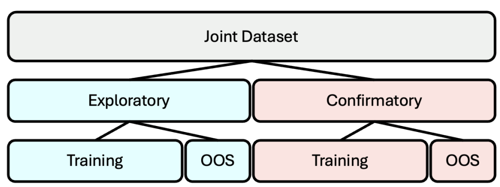

Fig. 3. Splitting the Dataset. Exploratory and confirmatory datasets were collected at the same time. Confirmatory data was not analyzed until a set of analyses were pinned down in the exploratory data. Together, these datasets comprise the Joint dataset. Both datasets were split into training and out-of-sample ("OOS") subsamples depending on trial number. Trial numbers divisible by 10 were designated as OOS. Remaining trials were designated as training data. Training data was used for model fitting. OOS data was used to check fitted model predictions.

Computational Model. To adjudicate among the accounts that survive our behavioral result, we developed a Hybrid Attentional Drift–Diffusion Model (Hybrid aDDM). The model is designed as a nesting framework rather than as a single competing hypothesis: it embeds the standard aDDM, additive attention models (AaDDM), range-normalized variants (RaDDM), and their combination as special cases (MARaDDM), so that the comparison among them is a comparison within a single likelihood. Decision-makers accumulate noisy evidence over value signals that may be range-normalized within each context prior to comparison. Range-normalization maps both gains and losses onto a common positive scale, removing the sign-reversal problem that arises for negative values in the standard aDDM. Attention influences evidence accumulation through two channels: a value-dependent mechanism that discounts the non-fixated option during comparison, and a value-independent mechanism that adds an attentional bias in favor of the fixated option. Once values are range-normalized, both mechanisms act in the same direction, jointly biasing accumulation toward the attended option and preserving attentional choice biases across gain and loss contexts.

Model parameters were estimated separately for each participant and condition using likelihood-based methods. Because the Hybrid aDDM nests multiple competing accounts, we used Bayesian model comparison to quantify support for alternative models of attentional influence. To evaluate whether fitted models captured key behavioral signatures, we simulated choices, response times, and fixation-dependent choice biases out-of-sample using the same lotteries encountered by participants. This approach allows us to assess not only in-sample fit, but also the ability of each model to generalize to unseen data. For more details, see Methods.

Basic Psychometrics

The top row of Fig. 4 depicts a psychometric curve, separately for each experimental condition (color), study (line type), and dataset (column). Table S1 contains associated statistical analysis. Choices were more sensitive to relative normalized expected value in Study 2 than in Study 1. This is likely due to the narrow range of $E[V]$ differences in Study 1 ($\Delta E[V] \in [-1, 1]$) compared to Study 2 ($\Delta E[V] \in [-4, 4]$). We found a small but significant increase in choice sensitivity to $\Delta E[V]$ in the Loss condition in Study 1, but this was not present in Study 2.

The middle row of Fig. 4 depicts response time ("RT") as a function of normalized choice difficulty. In both studies, as in previous literature, we replicated increasing RTs in choice difficulty (i.e. best minus worst value). In Study 1, RTs were not significantly different in the Loss condition, regardless of choice difficulty. In Study 2, RTs were on average 0.7 s slower in the Loss condition. This difference shrinks at a small but significant rate as choices become easier. We believe the slower RTs in the Study 2 Loss condition were partially driven by the difficulty of considering an implicit $0 outcome with a loss lottery, which some participants self-reported after the experiment concluded.

The bottom row of Fig. 4 depicts the number of fixations as a function of choice difficulty. As with RTs, the number of fixations did not significantly differ by condition in Study 1, while they increased by roughly 0.5 on average in the Loss condition in Study 2.

Overall, there was a negligible difference in the quality of choices between conditions in both studies. RTs did not significantly differ between conditions in Study 1, but they were significantly slower in the Loss condition in Study 2. Critically for what follows, this means that any difference in attentional choice biases across conditions could not be attributed to a difference in overall choice difficulty or decision quality.

For results regarding the attentional manipulation in Study 2, please refer to *Additional Text* in the supplementary.

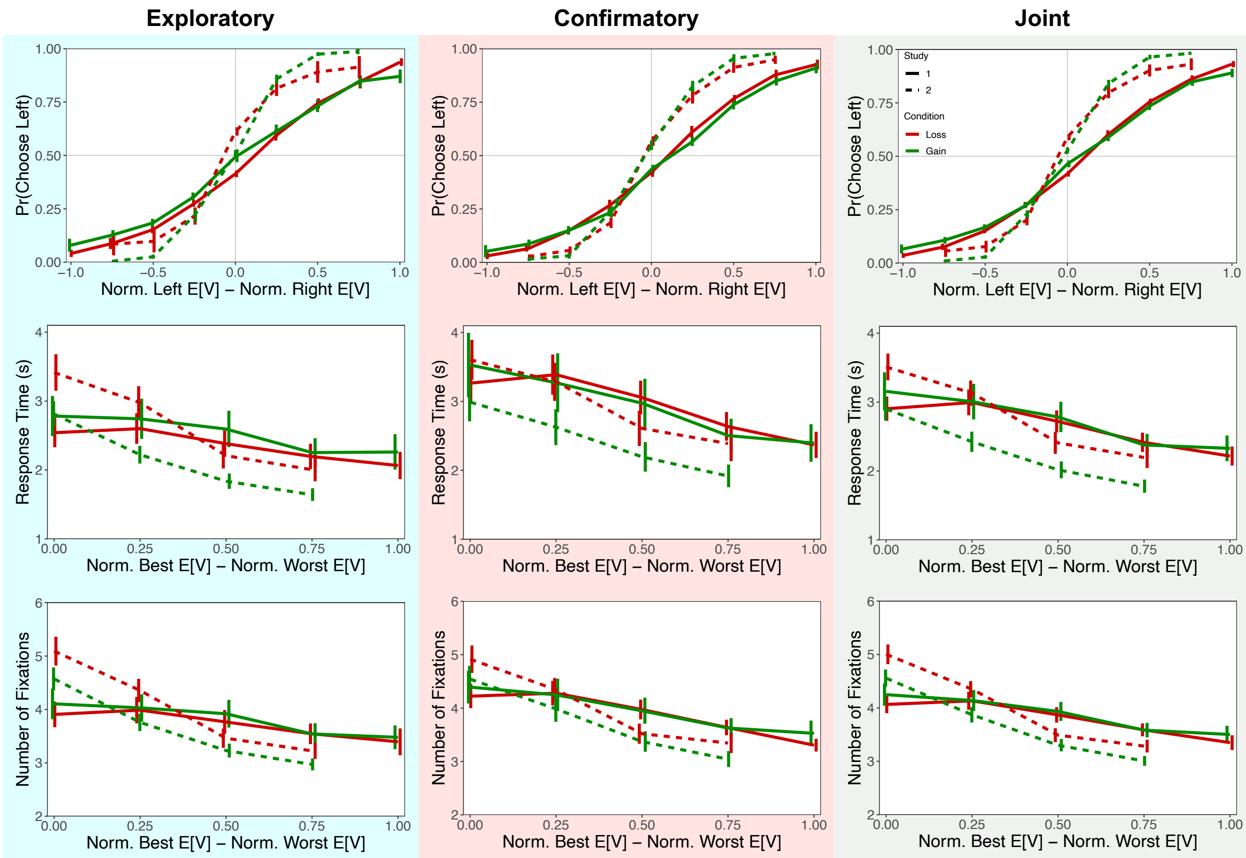

Fig. 4. Basic Psychometrics. The top row depicts the probability of choosing the left item as a function of the difference in normalized expected values between the left and right lotteries ("relative value"). "Norm.": Expected values were range-normalized within a context by subtracting the minimum expected value in that context, then dividing by the range in that context. The middle row depicts response time as a function of choice difficulty, measured by the difference between the normalized expected values of the best and worst lottery. The bottom row depicts the number of fixations as a function of choice difficulty. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

Fixation Process

Fig. 5 and Table S2 explore how the fixation process differs between the Gain and Loss condition in Studies 1 and 2.

The first row of Fig. 5 depicts the probability of first fixating on the best lottery as a function of choice difficulty. In both conditions in both studies, this probability remained at chance regardless of choice difficulty, suggesting proper counterbalancing of the location of stimuli.

The second row of Fig. 5 depicts mean fixation durations in the Gain and Loss conditions in both studies, separately for first, middle, and last fixations. In Study 1, there were no significant differences across conditions in mean fixation duration for any fixation type (First, Gain-Loss: $p = 0.29$; Middle, Gain-Loss: $p = 0.75$; Last, Gain-Loss: $p = 0.66$). But across all fixation types in Study 2, fixations in the Loss condition were slightly longer (First, Gain-Loss: $p = 0.02$; Middle, Gain-Loss: $p = 0.01$; Last, Gain-Loss: $p < 0.001$), though only by 30 to 50 ms on average. This is less than half the duration of a typical blink.

The third row of Fig. 5 depicts middle fixation duration as a function of choice difficulty. In both studies, middle fixation durations slightly increased in choice difficulty. In Study 1, middle fixation durations were not sensitive to condition, but in Study 2, they slightly increased in the Loss condition.

The fourth row of Fig. 5 depicts first fixation duration as a function of the normalized expected value of the first option. In Study 1, first fixation duration was not sensitive to the normalized expected value of the first fixated lottery or condition. In Study 2, first fixation duration increased in both the normalized expected value of the first fixated lottery and in the Loss condition.

The fifth row of Fig. 5 depicts net fixation duration to the left lottery as a function of left minus right normalized $E[V]$. In both studies, the relationship exhibits a significant positive relationship. In Study 2, participants tended to look right a bit more in the Loss condition compared to the Gain condition, but this pattern did not persist in Study 1. When lotteries had equal expected value, they were fixated about the same amount in Study 1, but the right-side lottery received significantly more attention in Study 2.

This right-side attentional favoritism occurred because participants most frequently utilized 2 fixations when the fixation cross started left, whereas they most frequently utilized 3 fixations when the fixation cross started right (see Fig. S1 and its associated Table S3). This phenomenon is not explained by Bayesian models of attention allocation.

Overall, there are small (but still significant) differences in fixation patterns between the Gain and Loss conditions in both studies. While there is significant attentional favoritism towards the right side option in Study 2, we do not see this reflected as a choice bias in the first row of Fig. 4, hinting that attention might be playing a smaller role in our risky choices compared to choices in other domains (S. M. Smith & Krajbich, 2018; Tavares et al., 2017).

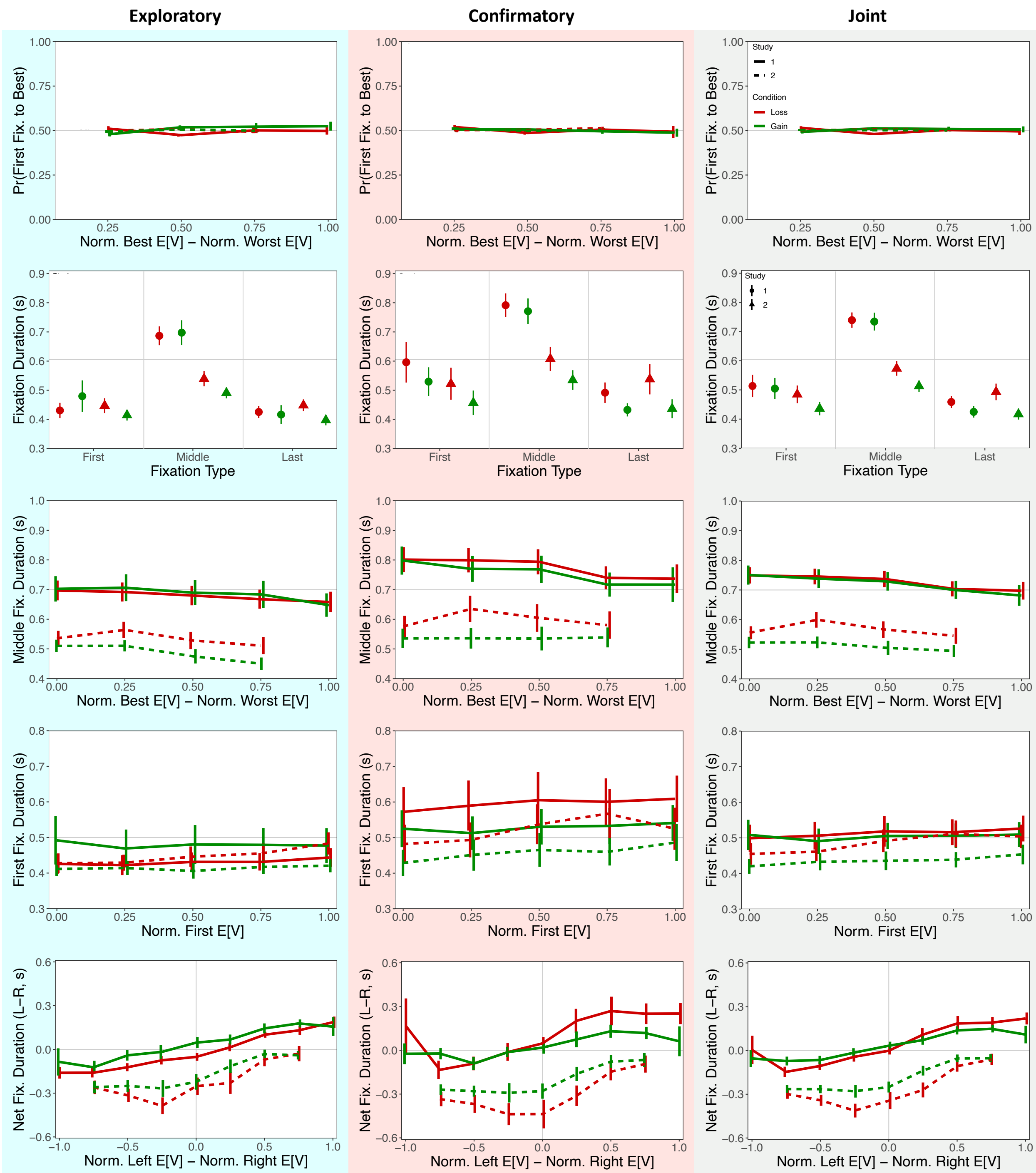

Fig. 5. Fixation Process. The first row depicts the probability of first fixating on the best lottery as a function of choice difficulty. The best lottery is determined by expected value, ignoring risk preferences. "Norm.": Expected values were range-normalized within context. The second row depicts fixation durations as a function of fixation type. The third row depicts middle fixation durations as a function of choice difficulty. The fourth row depicts first fixation durations as a function of normalized expected value of the first fixated option. The fifth row depicts net fixation duration to the left lottery as a function of its relative expected value. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

Attentional Choice Biases

We now turn to our central test: whether attentional choice biases reverse in aversive choices.

Fig. 6 and Table S4 present attentional choice biases across conditions and studies. The goal here is to characterize how attention affects our choices in the loss domain by comparing these attentional biases across gains and losses.

The top row of Fig. 6 depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery ("net fixation bias"). We corrected the probability by subtracting from each choice observation (1=left, 0=right) the proportion with which left was chosen at each ΔNorm.$E[V]$. Note that in the absence of an attentional bias, this relationship should be flat. Instead, we find evidence of net fixation bias in the Gain condition, consistent with previous literature. However, we predicted a reversal of this bias in the Loss condition based on predictions of the aDDM (see Fig. S2 row 1). In both studies, and in both the exploratory and confirmatory samples, we found no evidence of a reversal. The magnitude and direction of net fixation bias were indistinguishable across conditions.

In the bottom row of Fig. 6, we plot the probability of choosing the last fixated lottery as a function of the relative expected value of the last fixated lottery ("last fixation bias"). Note that in the absence of an attentional bias, the probability of choosing the last fixated lottery should cross 50% when the relative value of the last fixated lottery is 0. Replicating previous studies, we find evidence of last fixation bias in the Gain condition. Once again, contrary to our hypothesis, we do not observe a reversal of this bias in the Loss condition.

The relevant test statistics are the Loss-condition interaction terms in Table S4, none of which are significant in either study or in any sample. We emphasize that this is a failure to reject rather than a demonstration of exact equality. But the effect we hypothesized was not a subtle one. Under the standard aDDM, net fixation bias in the Loss condition (the slope) should have the opposite sign from the Gain condition, and the last fixation bias curve in the Loss condition should cross 50% on the opposite side of zero from the Gain condition (Fig. S2 row 1). What we observe instead is a bias of the same sign and comparable magnitude in both domains, replicated across two stimulus formats and two independently collected samples. This is the result that constrains the remainder of the paper.

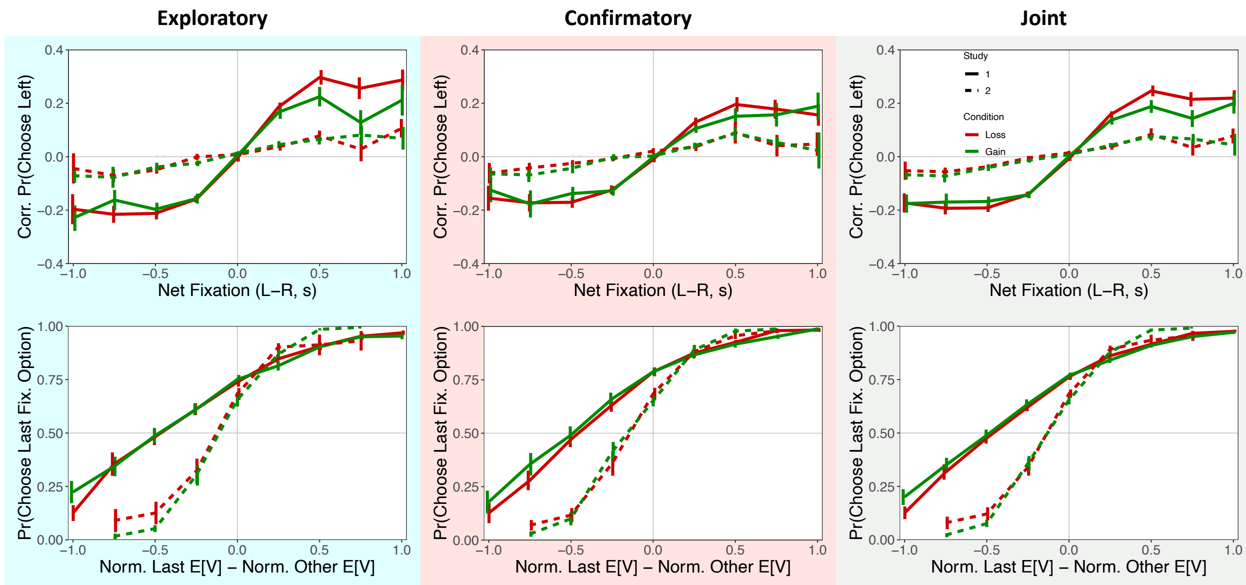

Fig. 6. Attentional Choice Biases. The top row depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. The corrected probability is computed by subtracting from each choice observation (1=left, 0=right) the proportion of which left is chosen at each relative value. The bottom row depicts the probability of choosing the last fixated lottery as a function of the relative normalized expected value of the last fixated lottery. "Norm.": Expected values were range-normalized within context. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

Model Selection

Given the results in Fig. 6, models of attention in binary choice must satisfy this requirement: attentional pull toward the attended option must be preserved when every option value is negative. In this section we work out which classes of model can and cannot meet that requirement, and then use a behavioral signature to discriminate among the survivors.

This behavioral signature immediately hints at a value-independent role of attention in the choice process that favors the attended option, like in the AaDDM. In row 4 of Fig. S2, we simulate behavior using the AaDDM and find that it is capable of predicting identical attentional choice biases across our conditions. Other explanations, like (a) selecting the opposite of the predicted choice or (b) accumulating over absolute values and selecting the opposite of the predicted choice, are incapable of this (see Fig. S2 rows 2 and 3).

An alternative explanation is that participants are range-normalizing values before integrating them to make a decision (Rangel & Clithero, 2012; Frydman & Jin, 2021; Soltani, De Martino, & Camerer, 2012). This would transform negative value signals to positive signals. Note that since the range in the denominators of the value signals can be factored into the drift rate, a DDM with range-normalized value signals will generate the same likelihood as a DDM with reference-dependent value signals, where the reference-point is equal to the minimum value. For our purposes, we limit our estimation to the former case, where expected values are range-normalized before entering the accumulation process. A model in which attention discounts range-normalized value signals (the RaDDM) reproduces identical biases across conditions, as does a model containing both mechanisms (the MARaDDM; see Fig. S2 rows 5 and 6).

The class that is eliminated is therefore well defined: models in which attention acts multiplicatively on unnormalized, signed value. Escaping this class requires either that attention's influence on accumulation not depend on the sign of value, or that the value signal entering the comparison process be sign-invariant. The AaDDM does the first. The RaDDM does the second. The MARaDDM does both simultaneously.

Before fitting the models and comparing likelihoods, there is one more test we can run to distinguish these explanations. Previous studies have recorded a negative relationship between overall value ($V_L + V_R$) and RTs (S. M. Smith & Krajbich, 2019; Shevlin, Smith, Hausfeld, & Krajbich, 2022; Ting & Gluth, 2025), and this relationship has been shown to follow directly from the multiplicative interaction between attention and value in diffusion models (Shevlin & Krajbich, 2021). In choices between gains, this relationship is consistent with the aDDM because of the value-dependent role of attentional discounting. For example, without loss of generality, suppose $d = 1$. Then the AaDDM would predict the same RT distribution for $V_L = V_R = 1$ as it would for $V_L = V_R = 10$, since RT is only dependent on the size of η and $(V_L - V_R)$. However, with attentional discounting (RaDDM or MARaDDM), evidence will accumulate faster when $V_L = V_R = 10$ compared to when $V_L = V_R = 1$, since the value of the non-fixated option is multiplied by $\theta \in (0, 1)$ during the value comparison process.

We can apply this same logic to choices between losses. If attentional effects are value-independent like in the AaDDM, then RTs and overall value should not show any correlation. If attentional effects are value-dependent and values are not normalized, then RTs will be decreasing as overall value moves further away from 0. But if participants are range-normalizing prior to evidence accumulation (like in the RaDDM or MARaDDM), then in losses, RTs will instead be decreasing as overall value moves closer to 0. Therefore, in aversive choices, the sign of the relationship between RTs and overall value serves as a distinguishing test between (a) the AaDDM and (b) the RaDDM and MARaDDM. In order to look for a negative relationship between RT and overall value, we run the following regression with mixed effects, separately for gains and losses:

$$log(RT) \sim \beta_0 + \beta_1 \left| \frac{V_L^{\text{Norm.}} - V_R^{\text{Norm.}}}{V_{max}^{\text{Norm.}} - V_{min}^{\text{Norm.}}} \right| + \beta_2 \left(\frac{V_L^{\text{Norm.}} + V_R^{\text{Norm.}} - 2V_{min}^{\text{Norm.}}}{V_{max}^{\text{Norm.}} - V_{min}^{\text{Norm.}}} \right) \tag{1}$$

and test if $\beta_2 < 0$. This is the same test used by S. M. Smith and Krajbich (2019), except with range-normalized values.

In Table S5, we simulate data using the AaDDM, RaDDM, and MARaDDM, then run the regression test from Eq. 1. Just like in gains, the AaDDM does not predict a relationship between RT and overall value in losses. However, both the MARaDDM and RaDDM predict a negative relationship in both gains and losses.

Table 1 repeats this regression test in our data, separately for each study and condition. For both studies, we find a significant, negative relationship between RT and overall value in the Loss condition. This evidence is consistent with our hypothesis that participants are integrating over range-normalized value signals during the value comparison process. We also replicate the negative relationship between RTs and overall value in the Study 1 Gain condition, but this relationship is not significant in the Study 2 Gain condition. For a visual representation of the RT–overall value relationship in our data, see Fig. S3. For replications of additional tests from S. M. Smith and Krajbich (2019), see Fig. S4.

Loss Condition

Dept. Var.	Indept. Var.	Exploratory Est.	SE		Confirmatory Est.	SE		Joint Est.	SE	
Study 1	β_0 Intercept	0.77	0.08	*	1.00	0.09	*	0.89	0.06	*
$log(RT)$	β_1 Abs. Diff. N. Val.	-0.21	0.03	*	-0.29	0.04	*	-0.25	0.02	*
(Linear)	β_2 Overall N. Value	-0.04	0.01	*	-0.03	0.02	*	-0.04	0.01	*
Study 2	β_0 Intercept	1.19	0.09	*	1.21	0.09	*	1.20	0.06	*
$log(RT)$	β_1 Abs. Diff. N. Val.	-0.67	0.05	*	-0.60	0.06	*	-0.63	0.04	*
(Linear)	β_2 Overall N. Value	-0.17	0.03	*	-0.11	0.03	*	-0.14	0.02	*

Gain Condition

Dept. Var.	Indept. Var.	Exploratory Est.	SE		Confirmatory Est.	SE		Joint Est.	SE	
Study 1	β_0 Intercept	0.81	0.10	*	0.95	0.11	*	0.88	0.07	*
$log(RT)$	β_1 Abs. Diff. N. Val.	-0.24	0.03	*	-0.34	0.05	*	-0.29	0.03	*
(Linear)	β_2 Overall N. Value	-0.05	0.01	*	-0.02	0.01		-0.03	0.01	*
Study 2	β_0 Intercept	0.84	0.07	*	0.89	0.10	*	0.86	0.06	*
$log(RT)$	β_1 Abs. Diff. N. Val.	-0.56	0.06	*	-0.52	0.06	*	-0.54	0.04	*
(Linear)	β_2 Overall N. Value	-0.03	0.02		-0.01	0.02		-0.02	0.02	

* indicates significance in all data sets at the 95% confidence level.
"Abs. Diff. N. Val.": Absolute difference of range-normalized values.
"Overall N. Value": Overall range-normalized value, the sum of range-normalized option values.

Table 1. Model Comparison Regression Test

We then fit the Hybrid aDDM separately for each participant in a study-condition, using the parameter grid specified in Fig. S5. This allows us to calculate the posterior model probabilities ("PMP") of the MARaDDM, RaDDM, and AaDDM, where the PMPs sum to 1 for each participant in a study-condition. In Fig. 7, we compare the PMPs of all three models across individuals using a probability simplex. We plot the PMP of the RaDDM as a function of the PMP of the MARaDDM. Note that the PMP of the AaDDM is equivalent to 1 minus the sum of the PMPs of the other models. This means that points close to the upper left corner of the triangle favor the RaDDM, points close to the lower right corner favor the MARaDDM, and points close to the lower left corner favor the AaDDM. We find that most participants are best-fit by either the AaDDM or MARaDDM in Study 1, and that most participants are best-fit by the RaDDM in Study 2. Fig. S7 shows these plots for the exploratory and confirmatory datasets.

Because the RaDDM and MARaDDM differ only in whether the additive attentional parameter η is free, this pattern has a simple reading: the value-independent component of attention is substantial in Study 1 and weak or absent in Study 2, whereas the value-dependent component is present in both. One plausible source of this difference is the stimulus format. In Study 1, lotteries were perceptual dot arrays whose value must be estimated from the display, a setting closer to the symbolic learning task in which additive gaze effects were originally reported (Cavanagh, Wiecki, Kochar, & Frank, 2014). In Study 2, expected value could be computed directly from the numbers on screen, leaving less room for a value-independent contribution of looking. Importantly, every model that survives our behavioral constraint retains range-normalized value encoding, so this variation concerns how much work attention does through each channel rather than whether values are normalized.

Since the Hybrid aDDM nests the RaDDM, AaDDM, and MARaDDM, in the next section, we will discuss model-based results using estimates from the full hybrid model (MARaDDM).

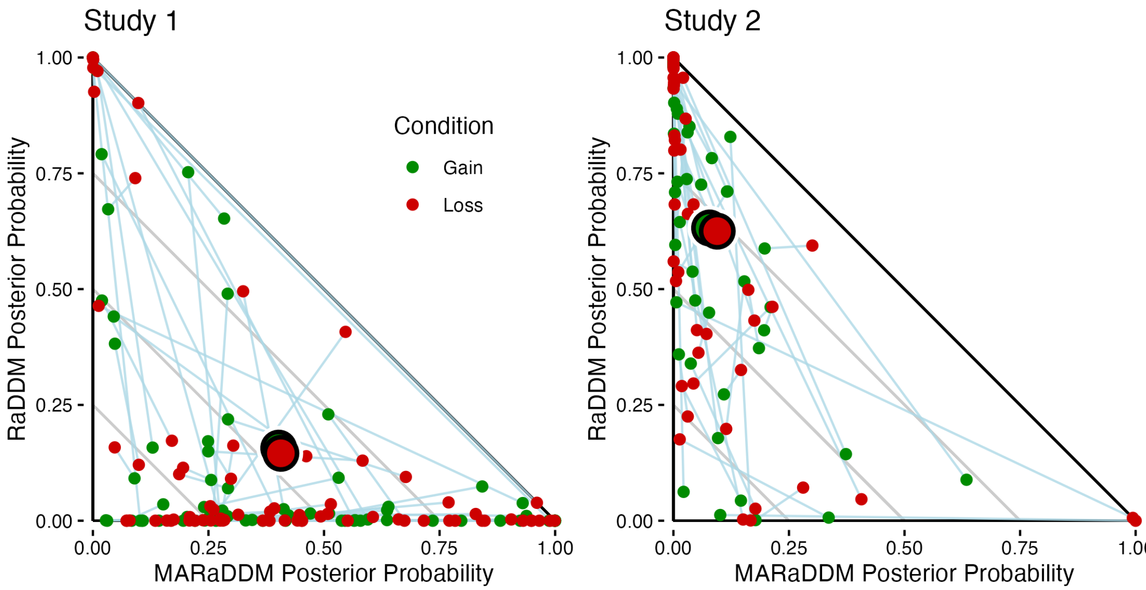

Fig. 7. Model Comparison. Posterior model probabilities of the RaDDM, MARaDDM, and AaDDM, plotted as a probability simplex. For each participant, the posterior model probability of the RaDDM is plotted as a function of the posterior model probability of the MARaDDM. The posterior model probability of the AaDDM for each individual is equal to 1 minus the sum of their posterior model probabilities for the RaDDM and MARaDDM. Points closer to the origin indicate participants that were best-fit by the AaDDM, points closer to the top-left indicate participants that were best-fit by the RaDDM, and points closer to the bottom-right indicate participants that were best-fit by the MARaDDM. Blue lines connect participants across conditions to visualize consistency of each participant's best-fitting model. Large dots indicate the mean coordinate across participants.

Hybrid aDDM

Fig. 8 presents the maximum a posteriori (MAP) estimates from the Hybrid aDDM. For each participant, we plot their estimate of $(d, \sigma, \theta, \eta, \lambda)$ in the Loss condition as a function of their respective estimate in the Gain condition. On average, in Study 1, $\eta_{1,G} = \eta_{1,L} = 0.0004$, and in Study 2, $\eta_{2,G} = \eta_{2,L} = 0.0001$. We also find that in Study 1, $\theta_{1,G} = 0.72$ and $\theta_{1,L} = 0.77$, and in Study 2, $\theta_{2,G} = 0.83$ and $\theta_{2,L} = 0.79$. Taken all together, these results suggest that attention plays two roles in the choice process, split between a value-dependent effect and a value-independent effect. Because range-normalization transforms all values to a positive space, both of these effects nudge choices towards the attended option. These effects did not significantly differ across conditions in either study ($\theta_{1,G} - \theta_{1,L} = -0.05$, Cohen's d $= -0.12$, $t(71) = -1.03$, $p = 0.31$; $\theta_{2,G} - \theta_{2,L} = 0.04$, Cohen's d $= 0.13$, $t(49) = 0.89$, $p = 0.39$; $\eta_{1,G} - \eta_{1,L} = 1e-5$, Cohen's d $= 0.05$, $t(71) = 0.40$, $p = 0.69$; $\eta_{2,G} - \eta_{2,L} = -2e-5$, Cohen's d $= -0.08$, $t(49) = -0.57$, $p = 0.57$).

Although η is small in absolute terms, the appropriate benchmark is the drift generated by value itself. With range-normalized values in $[0, 1]$ and $d_1 \approx 0.0006$ in Study 1, a typical relative value difference contributes roughly 0.0003 per time step, so $\eta_1 = 0.0004$ is of the same order as the value signal; in Study 2, where $d_2 \approx 0.0010$ and $\eta_2 = 0.0001$, the additive channel is roughly an order of magnitude weaker. This mirrors the model comparison in Fig. 7 and reinforces the conclusion that the additive channel carries real weight in Study 1 but little in Study 2.

Figs. S8 and S9 present the MAP estimates across participants for the RaDDM and AaDDM.

Compared to estimates from the RaDDM and AaDDM, the MARaDDM estimates θ closer to 1 and η closer to 0, suggesting lower levels of attentional bias from each of these sources ($\theta_{1,G}^{\text{MARaDDM}} - \theta_{1,G}^{\text{RaDDM}} = 0.51$, Cohen's d $= 2.15$, $t(71) = 18.23$, $p < 2e-16$; $\theta_{1,L}^{\text{MARaDDM}} - \theta_{1,L}^{\text{RaDDM}} = 0.55$, Cohen's d $= 2.28$, $t(71) = 19.38$, $p < 2e-16$; $\theta_{2,G}^{\text{MARaDDM}} - \theta_{2,G}^{\text{RaDDM}} = 0.16$, Cohen's d $= 1.01$, $t(49) = 7.11$, $p = 4e-9$; $\theta_{2,L}^{\text{MARaDDM}} - \theta_{2,L}^{\text{RaDDM}} = 0.19$, Cohen's d $= 1.03$, $t(49) = 7.30$, $p = 2e-9$; $\eta_{1,G}^{\text{MARaDDM}} - \eta_{1,G}^{\text{AaDDM}} = -6e-5$, Cohen's d $= -0.59$, $t(71) = -4.98$, $p = 4e-6$; $\eta_{1,L}^{\text{MARaDDM}} - \eta_{1,L}^{\text{AaDDM}} = -7e-5$, Cohen's d $= -0.66$, $t(71) = -5.62$, $p = 4e-7$; $\eta_{2,G}^{\text{MARaDDM}} - \eta_{2,G}^{\text{AaDDM}} = -5e-5$, Cohen's d $= -0.53$, $t(49) = -3.78$, $p = 4e-4$; $\eta_{2,L}^{\text{MARaDDM}} - \eta_{2,L}^{\text{AaDDM}} = -4e-5$, Cohen's d $= -0.41$, $t(49) = -2.91$, $p = 5e-3$). This makes sense because the role of attention in the MARaDDM is split, and both effects are nudging choices towards the attended option. In the RaDDM and AaDDM, these split effects are captured by a single attentional parameter, either θ or η, and therefore must be overestimated to account for both effects. In Fig. S10, we show that estimates of θ from the RaDDM and η from the AaDDM are significantly correlated across participants.

In Study 1, we did not observe differences in drift rates or noise across conditions. But in Study 2, we observed slightly smaller drift rates and noise in the Loss condition compared to the Gain condition ($d_{1,G} = 0.0006$ vs. $d_{1,L} = 0.0005$, $d_{1,G} - d_{1,L} = 5e-5$, Cohen's d $= 0.16$, $t(71) = 1.39$, $p = 0.16$; $d_{2,G} = 0.0011$ vs. $d_{2,L} = 0.0009$, $d_{2,G} - d_{2,L} = 0.0002$, Cohen's d $= 0.35$, $t(49) = 2.46$, $p = 0.02$; $\sigma_{1,G} = 0.017$ vs. $\sigma_{1,L} = 0.016$, $\sigma_{1,G} - \sigma_{1,L} = 0.001$, Cohen's d $= 0.21$, $t(71) = 1.77$, $p = 0.08$; $\sigma_{2,G} = 0.016$ vs. $\sigma_{2,L} = 0.014$, $\sigma_{2,G} - \sigma_{2,L} = 0.002$, Cohen's d $= 0.36$, $t(49) = 2.52$, $p = 0.02$). This is consistent with slower RTs found in Study 2's Loss condition compared to the Gain condition. We did not observe differences in rate of boundary collapse across conditions ($\lambda_{1,G} = 0.0002$ vs. $\lambda_{1,L} = 0.0002$, $\lambda_{1,G} - \lambda_{1,L} = 0$, Cohen's d $= 0.02$, $t(71) = 0.19$, $p = 0.85$; $\lambda_{2,G} = 2.5e-4$ vs. $\lambda_{2,L} = 2.1e-4$, $\lambda_{2,G} - \lambda_{2,L} = 4e-5$, Cohen's d $= 0.23$, $t(49) = 1.60$, $p = 0.12$).

Parameter recovery exercises for the Hybrid aDDM are presented in Fig. S6 and suggest that it is capable of successfully recovering (d, σ, θ, η, λ).

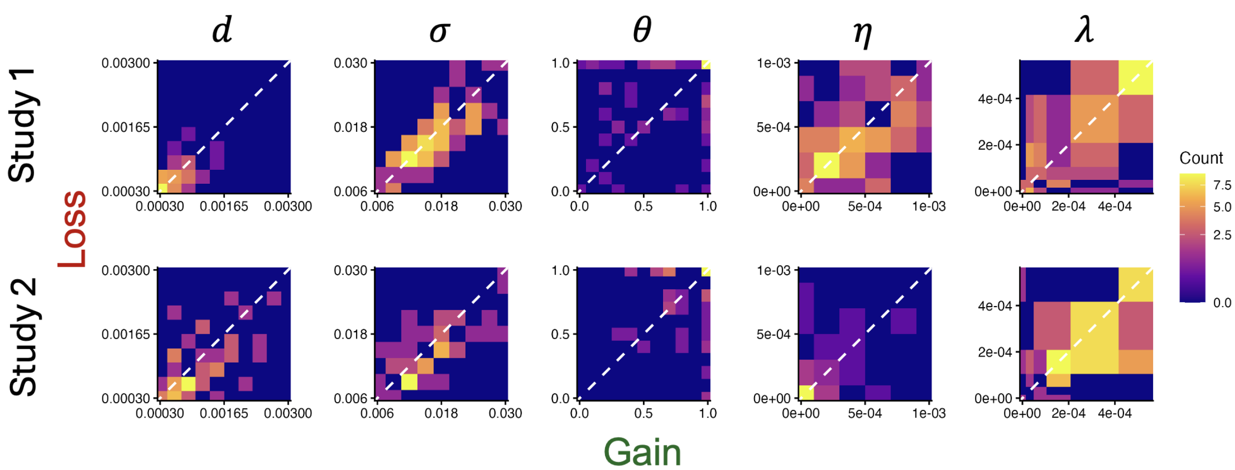

Fig. 8. Participant-Level Hybrid aDDM Estimates in the Joint Dataset. Estimates of the drift rate (d), noise (σ), multiplicative attentional bias (θ), additive attentional bias (η), and exponential barrier collapse (λ) in the Loss condition as a function of their counterpart in the Gain condition. White lines mark equality across the two conditions.

Out-of-Sample Simulations

To verify that the Hybrid aDDM is fitting our participants properly, we simulate behavior out-of-sample using the best-fitting parameters for each participant, separately for each condition. In Fig. 9, we compare simulated with observed out-of-sample behavior with a series of four plots: (i) the psychometric choice curve, as in Fig. 4 row 1; (ii) the RT curve, as in Fig. 4 row 2; (iii) the net fixation bias curve, as in Fig. 6 row 1; and (iv) the last fixation bias curve, as in Fig. 6 row 2. Our simulations show that the Hybrid aDDM is able to qualitatively match the average quality of choices, response times, and the degree of net and last fixation bias exhibited in our out-of-sample data. Figs. S11 and S12 show that the RaDDM and AaDDM are also capable of qualitatively matching out-of-sample behavior.

Because range-normalization is compressing a wider range of value signals into $[0, 1]$ space, it is crucial for the Hybrid aDDM to incorporate collapsing boundaries. Without this, simulated response times are over-estimated when value differences are close to 0 and under-estimated when absolute value differences are large.

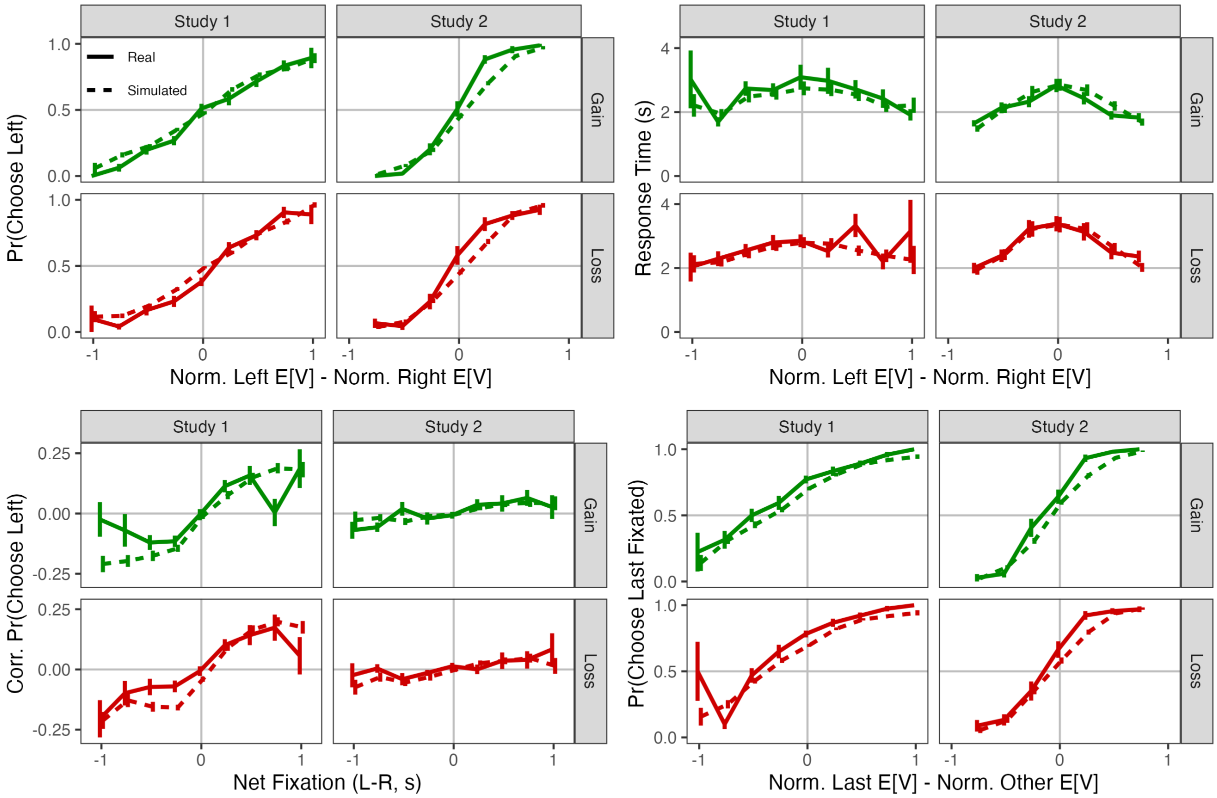

Fig. 9. Hybrid aDDM Out-of-Sample Predictions. (Top Left) The probability of choosing left as a function of the relative range-normalized expected value of the left option, as in Row 1 of Fig. 4. (Top Right) Response time as a function of the best minus worst range-normalized expected value, as in Row 2 of Fig. 4. (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. 6. 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 normalized expected value. (Bottom Right) The probability of choosing the last fixated option as a function of the normalized net expected value of the last fixated option, as in Row 2 of Fig. 6. Rows separate the data by condition, and columns separate by study. Out-of-sample data consists of trials that were multiples of 10 from all participants in joint dataset. 10 simulated datasets per participant. Error bars represent the standard error of the mean across all simulations for all participants.

Discussion

To investigate the role of attention in aversive decision-making, we conducted two binary risky choice experiments in which participants chose between lotteries involving either Gains or Losses. Across both studies, the overall quality of choice did not differ between conditions. In Study 2, but not Study 1, fixations were modestly longer in the Loss condition, consistent with prior evidence that aversive decisions elicit greater attentional engagement. Crucially, however, attentional choice biases (net fixation bias and last fixation bias) were indistinguishable across Gain and Loss conditions. This pattern is striking given that the standard Attentional Drift–Diffusion Model (aDDM) predicts a reversal of attentional biases when values are negative. Instead, our results indicate that attention consistently pulls choices toward the attended option, regardless of whether outcomes are appetitive or aversive.

We regard this null as the paper's primary contribution, because it eliminates a well-defined class of process models: those in which attention acts multiplicatively on unnormalized, signed value. This class includes the canonical aDDM and, by extension, any account that inherits its discounting mechanism without transforming the value signal first. Escaping the class requires one of exactly two features. Either attention must influence accumulation in a manner independent of the sign of value, or the value signal entering comparison must be sign-invariant. Our modeling exercise was designed to determine which of these features the data demand, and whether both are needed.

The evidence favors an account in which value signals are range-normalized prior to evidence accumulation and attention contributes through both channels. Three lines of evidence converge. First, the sign of the relationship between response times and overall value is negative in the Loss condition in both studies, a signature predicted by the range-normalized variants but not by a purely additive account. Second, formal model comparison assigns most participants to models retaining range normalization. Third, out-of-sample simulations reproduce the choice, response time, and fixation-bias curves in held-out trials. Together, these results suggest that sequential evidence accumulation operates over range-normalized values, and that attention plays multiple, complementary roles in the choice process.

Our account is complementary to, rather than in competition with, the proposal that attention modulates goal-relevant evidence rather than value (Sepulveda et al., 2020). That proposal was motivated in part by the observation that gaze is drawn to the preferred option when participants are asked to choose and to the non-preferred option when they are asked to reject, despite the two framings being logically equivalent (Mitsuda & Glaholt, 2014; van der Laan, Hooge, De Ridder, Viergever, & Smeets, 2015; Nittono & Wada, 2009). The two accounts operate at different levels of the same process: goal-relevance specifies *what* attention amplifies, whereas range normalization specifies *how* the value signal is encoded before attention acts on it. In a task where all outcomes are undesirable and the goal is to select the least bad option, the goal-congruent quantity and the range-normalized quantity are the same monotone transform of expected value, so the two accounts coincide behaviorally. What our results add is a specification of the encoding step, and one for which there is independent biological evidence: value-sensitive neurons in orbitofrontal cortex adapt their encoding to the range of values available in a given context (Padoa-Schioppa, 2009; Conen & Padoa-Schioppa, 2019), and this adaptation extends to the ranges of prospective gains and losses (Brochard & Daunizeau, 2024).

A different challenge comes from the proposal that the association between gaze and choice is partly post-decisional, arising after a covert commitment has been made rather than causing it (Zylberberg, Krajbich, & Shadlen, 2026). Such an account would predict our null trivially, since gaze that follows a completed decision is indifferent to the sign of option values. It is less well suited, however, to the net fixation bias we observe in both conditions (Fig. 6, top row), which reflects dwell time accumulated across the whole trial rather than gaze in the final moments before the response.

These findings have important implications for decisions involving aversive outcomes. Lejarraga, Schulte-Mecklenbeck, Pachur, and Hertwig (2019) documented an "attention–aversion gap," whereby individuals devote more attentional resources to aversive than to appetitive choices, independent of preferences. They argue that this asymmetry may have evolutionary roots: historically, losses often carried more severe consequences than gains. We replicate this pattern in our fixation data. Understanding how attention operates in such contexts is especially important given the prevalence of real-world aversive decisions, such as trade-offs between financial obligations and health expenditures, and may inform interventions that help individuals navigate unavoidable losses more effectively (Johnson et al., 2012).

At first glance, our results appear to contradict earlier findings showing that attention biases choices *away* from fixated options when decisions involve aversive stimuli or negative attributes (Armel et al., 2008; Krajbich, Lu, Camerer, & Rangel, 2012; Fisher, 2017). We suggest that this discrepancy reflects a fundamental distinction between *avoidable* and *unavoidable* aversive outcomes. When individuals can choose to avoid an aversive outcome altogether, it may be optimal to encode raw option values in order to evaluate valence accurately. By contrast, when aversive outcomes are unavoidable, as in our task, individuals may adopt a more optimistic evaluative frame, assessing options relative to a reference point near the minimum possible value. This transformation renders subjective values weakly positive and allows attention to continue biasing choices toward attended options. Both scenarios can be captured within the Hybrid aDDM framework, and the distinction generates a testable prediction for future work: within the same participants, attentional choice biases should reverse when an aversive outcome can be avoided and persist when it cannot.

This interpretation aligns naturally with query theory, which conceptualizes preference construction as a sequence of internally generated queries (Johnson, Häubl, & Keinan, 2007; Weber et al., 2007). Empirical work suggests that individuals often initiate this process by querying positive attributes (Weber & Johnson, 2006). In our task, participants may frame these queries optimistically, via range-normalization or reference-dependence, without sacrificing optimality, since any monotonic transformation of evidence preserves ordinal comparisons (see Callaway, Rangel, and Griffiths (2021) for a similar discussion on the duality of optimal sampling processes). Similarly, participants may mentally simulate outcomes during fixations (Busemeyer & Townsend, 1993), but frame those simulations relative to a contextual reference point (Tversky & Kahneman, 1992).

Our findings also connect to prior evidence of last-fixation bias in aversive risky choice. Brandstätter and Körner (2014) reported that choices coincided with the last fixated option in a majority of loss trials, though their analysis did not account for expected value. Incorporating value information helps reconcile these results with ours and suggests that attentional effects in aversive choice are more nuanced than in gains. In particular, the role of attention may vary across domains (e.g. food, consumer products, intertemporal choice, risk) and depend on decision-makers' goals (Krajbich, 2019; Thomas, Molter, Krajbich, Heekeren, & Mohr, 2019). The Hybrid aDDM provides a flexible framework for investigating these possibilities.

From a modeling perspective, our results imply that attention influences choice through both value-dependent and value-independent pathways, and that value signals are transformed prior to comparison. The value-independent pathway is consistent with causal evidence that manipulating attention shifts choice probabilities in favor of the attended option (Pleskac, Yu, Grunevski, & Liu, 2023; Bhatnagar & Orquin, 2022), and the transformation itself is consistent with computational and neural evidence suggesting that avoiding aversive outcomes is encoded as a positive value in the orbitofrontal cortex (Kim, Shimojo, & O'Doherty, 2006). More broadly, our findings align with models of efficient coding (Frydman & Jin, 2021; Polania, Woodford, & Ruff, 2019) and reference-dependence (O'Donoghue & Sprenger, 2018; Tversky & Kahneman, 1992), though they diverge from expectations-based reference-point models (Kőszegi & Rabin, 2009). Instead, they support reference-point rules that depend on the range of available outcomes, particularly the minimum value in context (Soltani et al., 2012; Garagnani & Vieider, 2025). Operationally, this resembles a MaxMin reference-point rule, which has been shown to be common in risky choice (Baillon, Bleichrodt, & Spinu, 2020). Within the DDM, such a rule is mathematically equivalent to range-normalization of outcomes prior to accumulation (Rangel & Clithero, 2012).

An alternative, complementary interpretation is that choice itself may confer a sense of control, thereby attenuating the subjective aversiveness of losses. Prior work shows that perceived control reduces the experienced intensity of aversive stimuli (Staub, Tursky, & Schwartz, 1971; Sanderson, Rapee, & Barlow, 1989). In our task, the presence of multiple options may grant participants a degree of agency, shifting subjective valuation in a positive direction. This interpretation is consistent with evidence that the ventromedial prefrontal cortex encodes the subjective value of control in both appetitive and aversive contexts (Wang & Delgado, 2019, 2021).

Relatedly, valuation in our task may involve an anchoring-and-adjustment process, whereby the minimum outcome serves as an anchor and subjective values adjust upward as outcomes are mentally simulated (Tversky & Kahneman, 1992; Cecchi, Gluth, & Palminteri, 2025). Recent evidence using artificial intelligence to infer utility functions further underscores the importance of contextual factors in shaping utility and probability weighting functions (Peterson, Bourgin, Agrawal, Reichman, & Griffiths, 2021; Plonsky et al., 2024).

Our study has several limitations. First, we impose range-normalization with the reference point fixed at the minimum expected value in each context rather than estimating it, so our results establish that a sign-invariant value signal is required without pinning down the precise transformation. Second, we focus exclusively on binary choice, whereas many real-world decisions involve multiple alternatives (Krajbich & Rangel, 2011; Thomas, Molter, & Krajbich, 2021; Leng, Frömer, Summe, & Shenhav, 2024). Third, attentional mechanisms may differ in more complex environments, such as lotteries with multiple outcomes or richer attribute structures (Oprea, 2024; Gonçalves, 2024), and our model treats fixations as exogenous rather than modeling how attention is allocated (Gluth, Deakin, & Rieskamp, 2024; Callaway et al., 2021). Fourth, while we examine risky monetary choices, aversive decision-making spans many domains, including food, social interactions, health, and politics. Future work should assess whether similar attentional dynamics operate across these settings.

In summary, attention plays a robust role in aversive choice, and it does not reverse. Contrary to the predictions of standard process models, attention to an aversive option nudges choice toward that option, in two studies and two independently collected samples. This result rules out models in which attention acts multiplicatively on unnormalized, signed value, and supports the view that individuals accumulate evidence over range-normalized values while attention contributes through both value-dependent and value-independent mechanisms. Together, these findings offer a unified account of attentional influences across appetitive and aversive decision-making.

Methods

Tasks

To investigate the role of attention in the aversive choice process, we ran two eye-tracking studies involving binary risky choices: one using perceptual lottery representations and one using numerical representations to rule out strategy switching (see Fig. 2). Both studies were split equally into Gain or Loss condition where participants either chose from positive- or negative-outcome lotteries.

In **Study 1**, participants began the trial with a forced fixation cross in the center of the screen for 1 s. In the Gain condition, participants were presented with two grey circles on the left and right sides of the screen. Inside each circle were 100 green or white dots. The number of white dots represented the probability of receiving nothing; the number of green dots represented the probability of gaining \$10. Participants were given free response time to select the lottery they preferred with the arrow keys. After selecting, they were given feedback about their choice for 1 s. In the Loss condition, trials were similar, except the green dots were replaced with red dots representing the probability of losing \$10. In all trials, the probability of winning or losing was drawn from a uniform distribution over integers between 45 and 55.

Participants completed 400 trials, split into 2 blocks of 200 trials each. One block was in the Gain condition, the other in the Loss condition, with order counterbalanced. After the experiment was over, participants drew a number between 1 and 200 out of an urn. The lottery associated with this number in blocks 1 and 2 was played out. Participants were paid a $40 show-up fee, and gains (losses) earned from the experiment were added to (deducted from) this amount.

One potential issue with presenting lotteries as perceptual stimuli is that participants can easily switch between accumulating different types of evidence. For instance, participants might compare the ratio of green to white dots in the Gain condition, then switch to comparing the number of white dots in the Loss condition. Both strategies can arrive at the optimal solution, but would have different implications for the role of attention in the choice process. To check that this evidence switching was not happening, we ran a second study with numerical representations of the lotteries.

In **Study 2**, participants began the trial by fixating for 1 s on a fixation cross that could appear on the left, middle, or right side of the screen. In the Gain condition, participants were presented with two lotteries in green. Lotteries comprised a positive outcome and probability p of earning that outcome, with an implicit $0 outcome with probability $1-p$. Absolute outcomes were bounded between $6 and $12, and differences in expected value of the lotteries were bounded between -$4 and $4. Lottery outcomes and probabilities were designed to prevent stochastic dominance of a choice. For instance, if lottery Left had a better outcome than lottery Right, then its probability was strictly bounded above by the probability in lottery Right. Thus, choices were always between a higher amount with lower probability and a lower amount with higher probability. Participants indicated their choices using the arrow keys and were free to respond at their own pace. Upon selecting an option, feedback about the selected option was presented for 1 s.

Participants completed 340 trials, split into 4 blocks of 85 trials each. Two blocks were in the Gain condition, and the others in the Loss condition, with order counterbalanced. After the experiment was over, participants drew two numbers between 1 and 170 out of an urn, with replacement. The first number represented a trial in the Gain condition, the second represented a trial in the Loss condition, and the lotteries in those trials were played out. Participants were paid a $40 show-up fee, and gains (losses) were added to (deducted from) this amount.

Four random trials per block were sanity check trials where there was clearly an option with higher expected value. In the Gain condition, the options were (i) $10 with $p = 1$ or (ii) $0 with $p = 1$. In the Loss condition, the options were (i) $0 with $p = 1$ or (ii) -$10 with $p = 1$. If participants chose option (ii) on one of these trials, we counted it as one failed sanity check. We use these sanity checks to filter out inattentive participants (see *Participants* below).

The 81 remaining trials that were not sanity checks were equally split into 3 attentional manipulation conditions, where the fixation cross was positioned on the left, center, or right side of the screen to manipulate where participants first fixated.

Participants

As a pre-commitment to high-quality data, we filtered out participants at the data collection stage if they were missing more than 10% of fixation data. Eye-tracking data may fail to record if participants are squinting or excessively moving or blinking. In Study 2, we also filtered out participants who failed more than 25% of our sanity check trials. These criteria were fixed before analysis and applied identically to the exploratory and confirmatory samples.

A total of 160 participants were recruited from Caltech and the surrounding community using flyers. We pre-screened participants against requiring glasses for vision correction that might interfere with eye tracking. Ninety-one participants were recruited to Study 1, of which 19 were excluded for failing our participant filter, leaving 72 participants (age: mean = 25 years, min = 18, max = 41; gender: 26 male, 45 female, 1 non-binary; ethnicity: 27 Asian, 3 Black, 10 Hispanic, 3 Middle Eastern, 0 Native American, 28 White, 1 Abstain). The first 36 participants were allocated to the exploratory sample, and the other 36 to the confirmatory sample (see *Inference Strategy*).

Sixty-nine participants were recruited to Study 2. Six were excluded due to a change in the instructions and 13 were excluded for failing the participant filter, leaving 50 participants (age: mean = 27.68 years, min = 18, max = 55; gender: 13 male, 34 female, 3 non-binary; ethnicity: 17 Asian, 5 Black, 10 Hispanic, 1 Middle Eastern, 1 Native American, 16 White, 0 Abstain). The first 25 participants were allocated to the exploratory sample, and the other 25 to the confirmatory sample.

The number of participants and trials per participant were chosen based on related studies using the same paradigm and modeling approach, which have shown that samples of this size and several hundred trials per participant provide reliable estimates of the parameters and effects of interest (Krajbich et al., 2010; S. M. Smith & Krajbich, 2018; Eum et al., 2023). Because our design allocates participants across two independent samples, each of our two studies additionally provides an internal replication at roughly half this size. All participants gave informed consent, and all experiments were approved by Caltech's Institutional Review Board.

Eye-Tracking

Eye-tracking data was collected using an Eyelink 1000 sampling at 500 Hz. Participants were instructed to sit approximately 60 cm from a 1920 × 1080 pixel monitor. Study 1 was coded in Psychtoolbox (Kleiner et al., 2007) and used lottery stimuli and ROIs that were 300 × 300 pixels. Study 2 was coded in PsychoPy (Peirce et al., 2019) with text height set to 108 pixels and ROIs set to 384 × 432 pixels. For Study 2, we used recorded response times to make a slight correction to last fixations due to a short lag in "stop recording" communication from PsychoPy to Eyelink. These corrections were typically around 5 ms. Fixations to the left ROI (lottery stimulus) were classified as "left", those to the right as "right", and outside the two ROIs as "blank". Sometimes, a sequence of blank fixations would occur between two fixations of the same type (e.g. right–blank–blank–right). These were re-coded as fixations to the same ROI since such sequences are typically due to eye-tracker noise or blinking and tend to be brief. If a sequence of blank fixations was recorded between different types of fixations (e.g. left–blank–blank–right), then they were coded as a saccade period between fixations.

Inference Strategy

As an alternative to pre-registration, we collected two separate datasets (see Fig. 3). The first (**exploratory**) dataset was used to explore the data and pin down our analyses. We then attempted to replicate the results from the exploratory dataset in the second (**confirmatory**) dataset, which was not analyzed until the analysis plan had been fixed. We report results separately for the exploratory and confirmatory datasets throughout the paper, so that every reported effect can be evaluated against an internal replication. This is a deliberate design choice given that our central claim is the absence of a predicted effect: a null obtained through undisciplined analysis would carry little weight, whereas a null that reproduces in a held-out sample collected under an identical protocol is considerably more informative.

In the spirit of meta-analysis, if results from the exploratory and confirmatory datasets were similar, we also report results on the pooled sample ("Joint") and describe summary statistics using joint estimates. Similar strategies across different fields have been used to promote replicability and prevent overfitting (see "Inference Strategy" in Eum et al. (2023) and "train–validation set vs. hold-out set" in Ludwig and Mullainathan (2024)).

Computational Model

We develop a variation of the Attentional Drift–Diffusion Model (aDDM) by Krajbich et al. (2010), which we call the Hybrid aDDM. Like the aDDM, value comparison is affected by gaze location, but the role of attention is split into two components. The purpose of the Hybrid aDDM is to serve as a nesting framework: because it embeds each of the candidate accounts described in the Results as a parameter restriction, the comparison among them can be carried out within a single likelihood rather than across separately specified models.

In the Hybrid aDDM, decision-makers integrate noisy value signals into an accumulator (RDV_t) that evolves over time. The accumulator initializes at $RDV_0 = 0$, ignoring any bias toward choosing options presented on the left or right sides of the screen. Decision boundaries collapse according to $e^{-\lambda t}$, where λ is an exponential decay rate. For examples of collapsing boundaries in sequential sampling models, see Churchland, Kiani, and Shadlen (2008); Hawkins, Forstmann, Wagenmakers, Ratcliff, and Brown (2015); Malhotra, Leslie, Ludwig, and Bogacz (2017); Glickman and Usher (2019); P. L. Smith and Ratcliff (2022). Note that at $t = 0$, decision boundaries initialize at ± 1. Once RDV_t crosses a boundary, a choice is made based on which boundary is hit: the upper boundary corresponds to choosing the left option and the lower boundary to choosing the right option. The accumulator evolves according to:

$$RDV_t = RDV_{t-1} + \mu_t + \epsilon_t, \tag{2}$$

where ϵ_t is i.i.d. Gaussian noise with variance σ^2. At each moment, the drift depends on gaze location:

$$\mu_t := \begin{cases} d[f(V_L) - \theta f(V_R)] + \eta & \text{if looking left} \\ d[\theta f(V_L) - f(V_R)] - \eta & \text{if looking right} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Here, d controls integration speed, $f(V_i)$ encodes the value of option $i \in \{L, R\}$, $\theta \in [0, 1]$ captures multiplicative attentional discounting of the nonfixated option, and $\eta \geq 0$ captures value-independent additive attentional bias.

The Hybrid aDDM treats fixations as exogenous and does not model the fixation process itself, though variants of the aDDM with endogenous fixation exist (Gluth, Kern, Kortmann, & Vitali, 2020; Towal, Mormann, & Koch, 2013; Callaway et al., 2021; Gluth et al., 2024).

Value in the Hybrid aDDM is range-normalized prior to entering the integration process. Prior computational models have also incorporated range-normalization before value comparison (Cecchi et al., 2025). This timing of range-normalization in the value construction process is consistent with prior literature on efficient coding of subjective value (Polania et al., 2019; Frydman & Jin, 2021), where value is encoded as a latent representation before being used in a decision rule, and with neural evidence that value coding adapts to the range of values available in a context (Padoa-Schioppa, 2009; Conen & Padoa-Schioppa, 2019). Functionally, range-normalization and efficient coding of subjective value generate similar behavioral predictions, though subtle differences do exist (see Frydman and Jin (2021) for details). Here, we assume that participants are range-normalizing expected value (V) within a context (c):

$$f(V_i) = \frac{p_i u_i - \mathrm{V}_c^{\min}}{\mathrm{V}_c^{\max} - \mathrm{V}_c^{\min}}, \tag{4}$$

where p_i is the probability of outcome u_i, and $\mathrm{V}_c^{\min}$ and $\mathrm{V}_c^{\max}$ denote the minimum and maximum expected values in condition $c \in \{\text{Gain}, \text{Loss}\}$. In Study 1, ($\mathrm{V}_{\text{Gain}}^{\min} = 4.5$, $\mathrm{V}_{\text{Gain}}^{\max} = 5.5$) and ($\mathrm{V}_{\text{Loss}}^{\min} = -5.5$, $\mathrm{V}_{\text{Loss}}^{\max} = -4.5$). In Study 2, ($\mathrm{V}_{\text{Gain}}^{\min} = 1$, $\mathrm{V}_{\text{Gain}}^{\max} = 6$) and ($\mathrm{V}_{\text{Loss}}^{\min} = -6$, $\mathrm{V}_{\text{Loss}}^{\max} = -1$). We fix the reference point to the minimum expected value in context rather than estimating it, so that the normalization is determined by the design rather than by fit.

Due to its flexible value encoding and two attentional parameters, the Hybrid aDDM nests multiple variations of the Drift–Diffusion Model ("DDM"). If $\theta = 1$ and $\eta = 0$, the model reduces to the standard DDM ("DDM") (Gold & Shadlen, 2007; Ratcliff & McKoon, 2008). If $\theta \in [0, 1)$ and $\eta = 0$, the model reduces to the standard aDDM (Krajbich et al., 2010, 2012). If we also apply a range-normalizing value function, then we call this the "RaDDM". If $\theta = 1$ and $\eta > 0$, the model reduces to the additive model of attention ("AaDDM") (Cavanagh et al., 2014; S. M. Smith & Krajbich, 2019). If $\theta \in [0, 1)$ and $\eta > 0$, then the model has both multiplicative and additive attentional roles, and we call this the "MARaDDM". Note that the RaDDM and MARaDDM differ only in whether η is free, so their relative posterior probabilities index the contribution of the value-independent channel.

Hybrid aDDM Fitting

Within our exploratory and confirmatory datasets, we also split our data into training and out-of-sample data. If the trial number was a multiple of 10, then it was designated as out-of-sample (see Fig. 3). All remaining trials were allocated to the training data. We fit the Hybrid aDDM to the training sample using a version of the ADDM Julia Toolbox (Enkavi, Goldman, Yang, & Rangel, 2024), but translated to Python. The toolbox discretizes both the time and state space of the accumulation process and uses a forward Euler estimation process to calculate likelihoods. The toolbox supports custom likelihood functions, discrete marginal posteriors, and Bayesian model comparison. Similar toolboxes have recently emerged and have been shown to robustly recover parameters (Liu, Fengler, Frank, & Harrison, 2025). Additional details are available at `https://addm-toolbox.github.io/dev/`.

Because evidence in the model varies moment-to-moment, the likelihood function does not have a closed-form solution and must be approximated numerically. Time was discretized at $dt = 10$ ms, and the accumulator state space was discretized with $dx \approx 0.05$. Parameter estimation was conducted via grid search over reasonable parameter ranges (see Fig. S5). Note that the units of d and η are per time step, so that the additive attentional bias should be interpreted relative to the drift generated by value at the same time scale rather than in absolute terms. Non-decision time ("NDT") was fixed to the latency to first fixation. NDT and saccade durations were summed for each trial and added to the final accumulation time to calculate the likelihood of the response time. Parameter recovery exercises with this configuration of the toolbox indicated good recovery of data-generating parameters (see Fig. S6).

Out-of-Sample Simulations

After fitting the Hybrid aDDM to the training data, we simulated behavior and compared this to out-of-sample data. For each participant and condition, we simulated 10 datasets using the same lotteries encountered during out-of-sample trials. Fixation duration statistics were sampled from empirical distributions, conditional on the Gain or Loss condition. Response times were constructed by adding sampled latency-to-first-fixation and saccade durations to the simulated accumulation time.

Regressions

All regression results reported in the paper are based on mixed-effects regressions. Regressions were implemented in R version 4.3.1 (R Core Team, 2023) using the `lme4` package (Bates, Mächler, Bolker, & Walker, 2015) with a quadratic approximation optimizer ("BOBYQA") and maximum iterations set to 2×10^5 where necessary. The code package and data for this paper can be found at `rnl.caltech.edu`.

Author Contributions AR and BE designed the research; SG and BE collected data; BE analyzed the data; and BE and AR wrote the paper.

Funding The authors gratefully acknowledge support from the NOMIS Foundation and NIMH grant R01MH134845.

Acknowledgments We thank Zeynep Enkavi for her immense help with the aDDM Toolbox in Julia, and Colin Camerer and Blair Shevlin for very useful comments.

Competing Interests The authors declare that they have no competing interests.

Open Practices Data and code are available at (`www.rnl.caltech.edu`). The design and analysis plans for this study were not preregistered, but the study includes an out-of-sample replication (see Methods for details).

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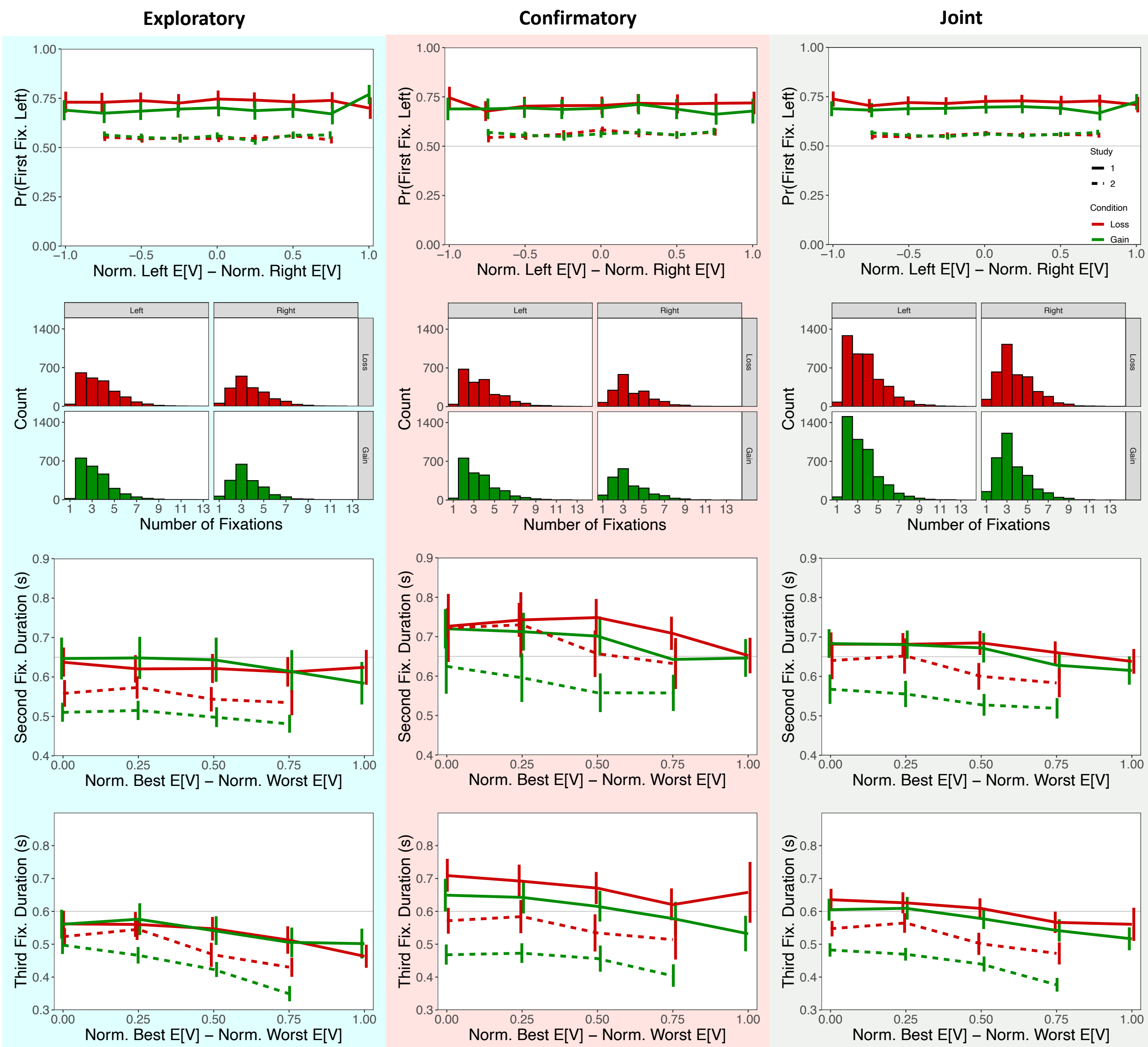
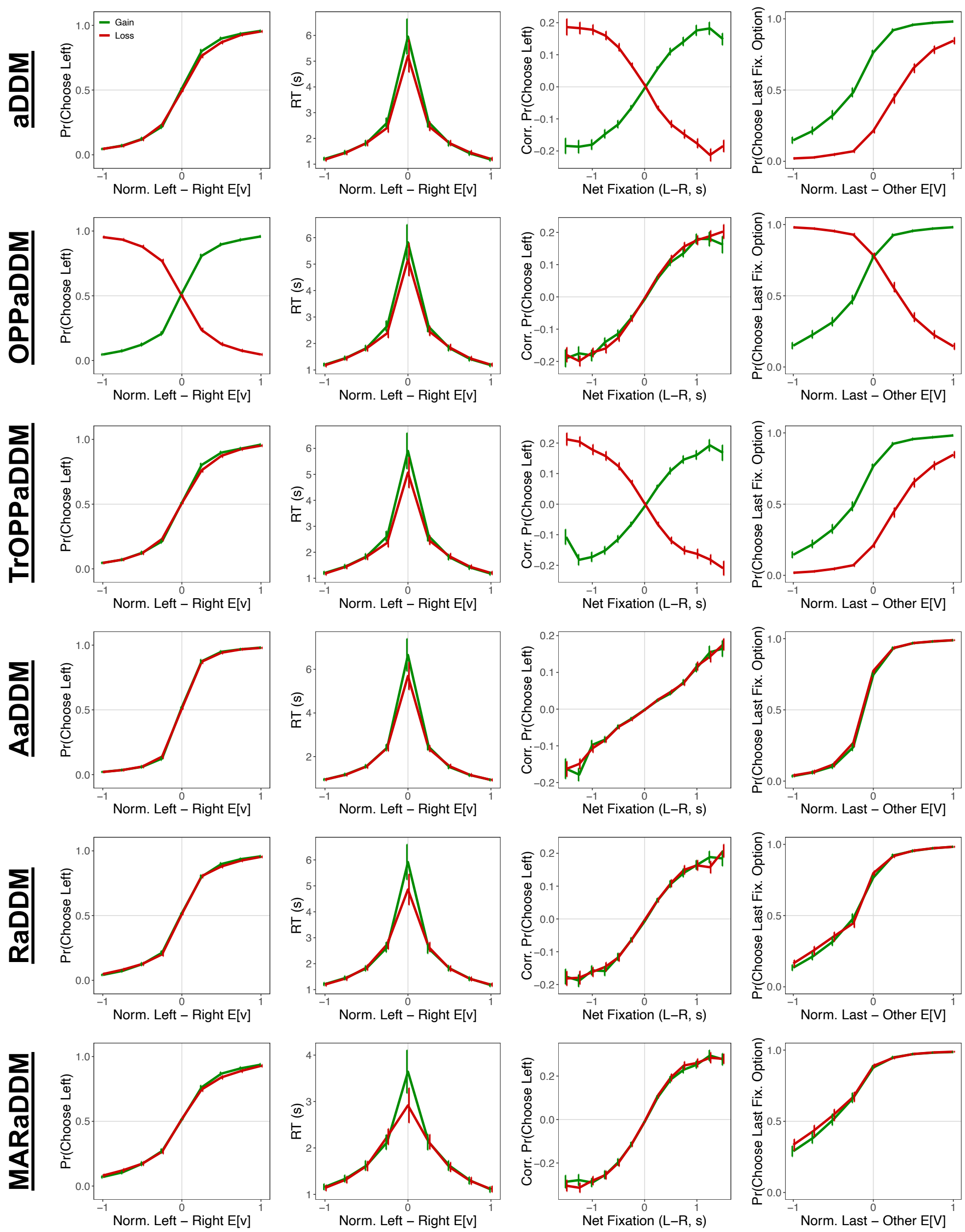
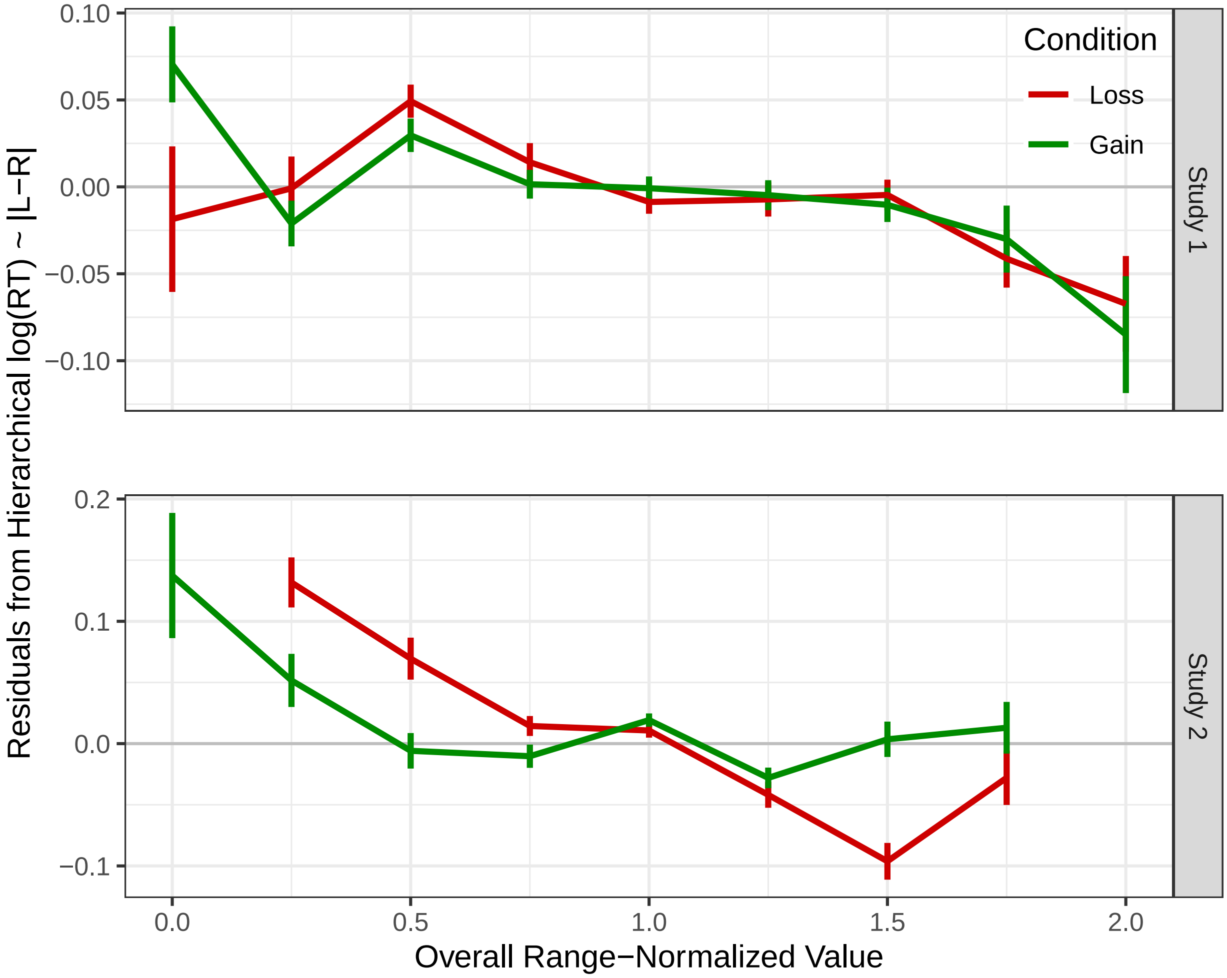
Supplementary Material



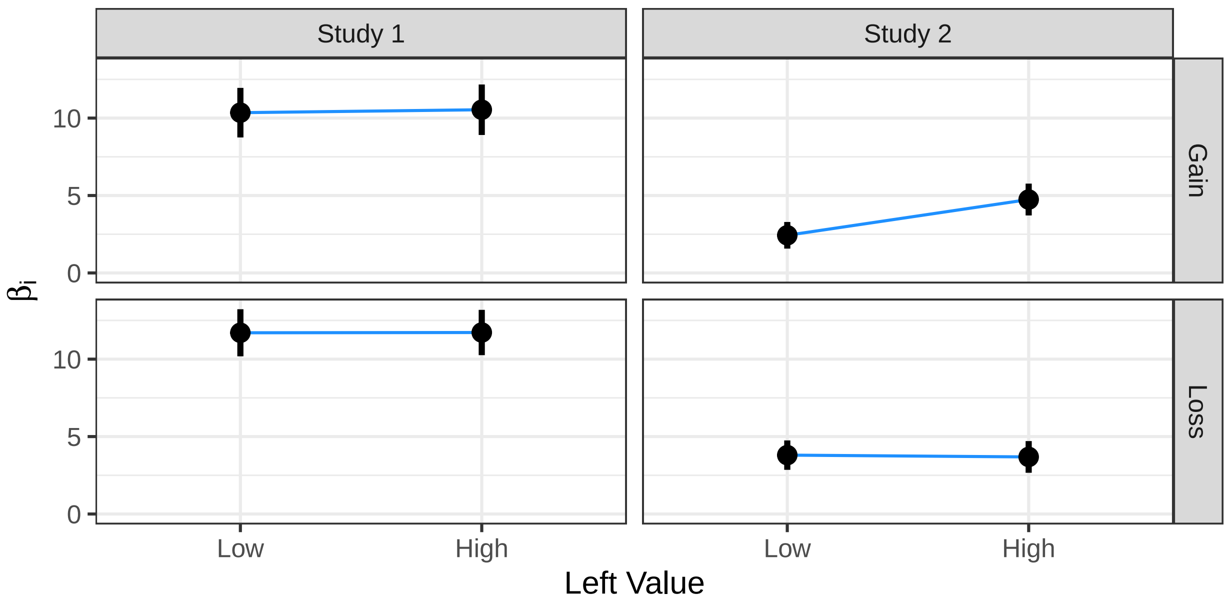
Supplementary Fig. 1. Additional Fixation Properties. The first row depicts the probability of first fixating left as a function of the relative value of the left option. "Norm.": Expected values were range normalized within context. The second row pools over all subjects in Study 2 and depicts histograms of the number of fixations in a trial, separately by condition and the location of first fixation. The third row depicts the second fixation duration as a function of choice difficulty. The fourth row depicts the third fixation duration as a function of choice difficulty. Error bars denote standard error of the mean across participants.



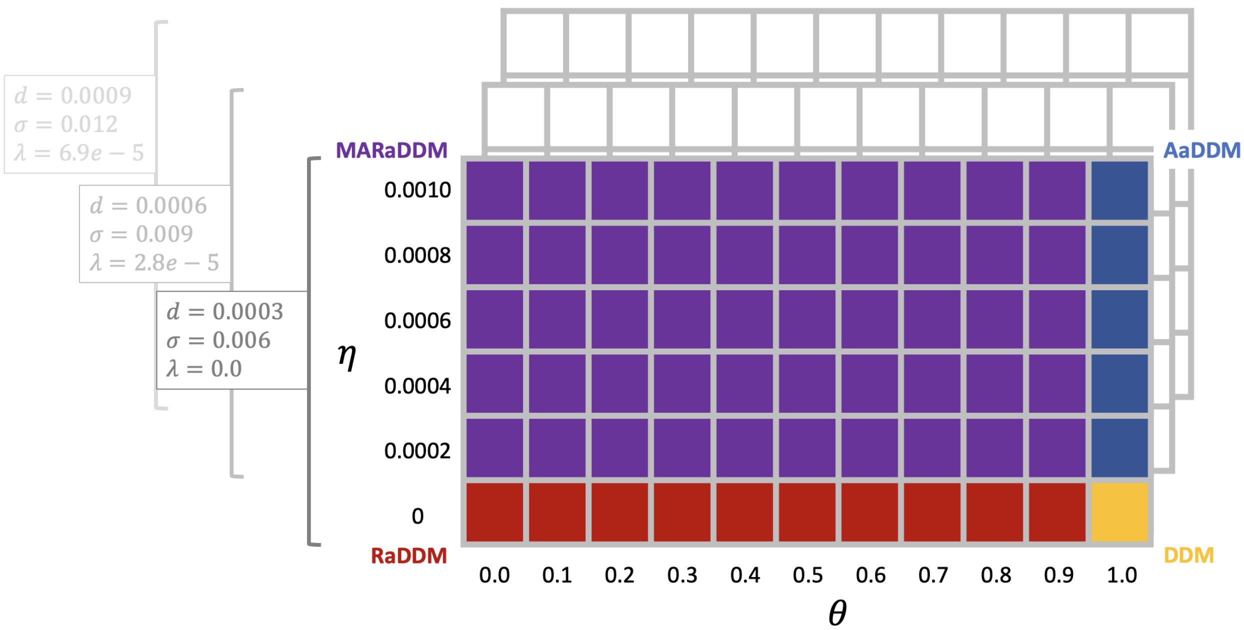
Supplementary Fig. 2. Simulations of Attentional Choice Biases. For each model and condition, we generated a simulated dataset of 200 trials for each of 25 simulated subjects, using the best-fitting estimates from the exploratory dataset. (Column 1) the psychometric choice curve, (Column 2) the RT curve, (Column 3) the net fixation bias curve, and (Column 4) the last fixation bias curve. For details, see Figs. 4 and 6. (Row 1) Data simulated using the aDDM with $\theta \in (0, 1)$. (Row 2) Data simulated using aDDM with final choice = opposite of barrier hit. (Row 3) Data simulated using aDDM with absolute value signals and final choice = opposite of barrier hit. (Row 4) Data simulated using AaDDM with $\eta \in [0.001, 0.010]$. (Row 5) Data simulated using RaDDM with $\theta \in (0, 1)$. (Row 6) Data simulated using MARaDDM with $\theta \in (0, 1)$ and $\eta \in [0.001, 0.010]$. Error bars denote the standard error of the mean across simulated subjects.



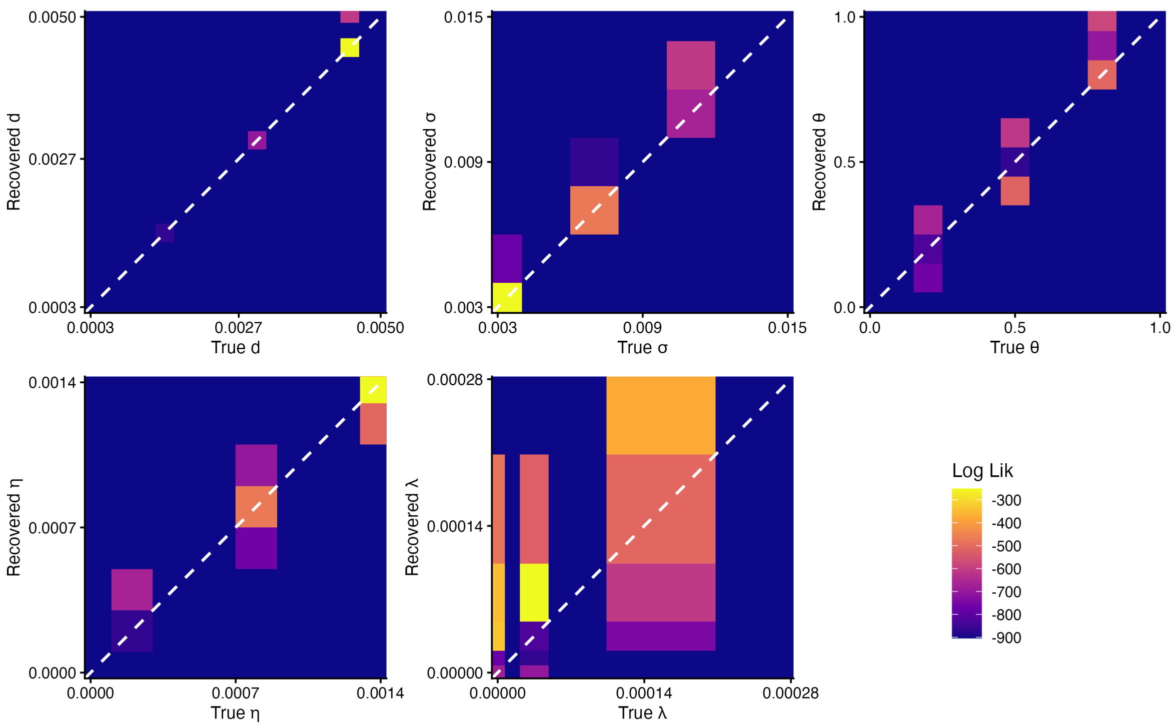
Supplementary Fig. 3. Relationship between Response Time and Overall Normalized Value. We run a mixed effects regression of log(RT) on the absolute difference between the left and right range-normalized expected values. Then, we plot the residuals as a function of overall normalized value of the choice, separately for study 1 and 2. Error bars denote the standard error of the mean across participant means. Data from the joint dataset.



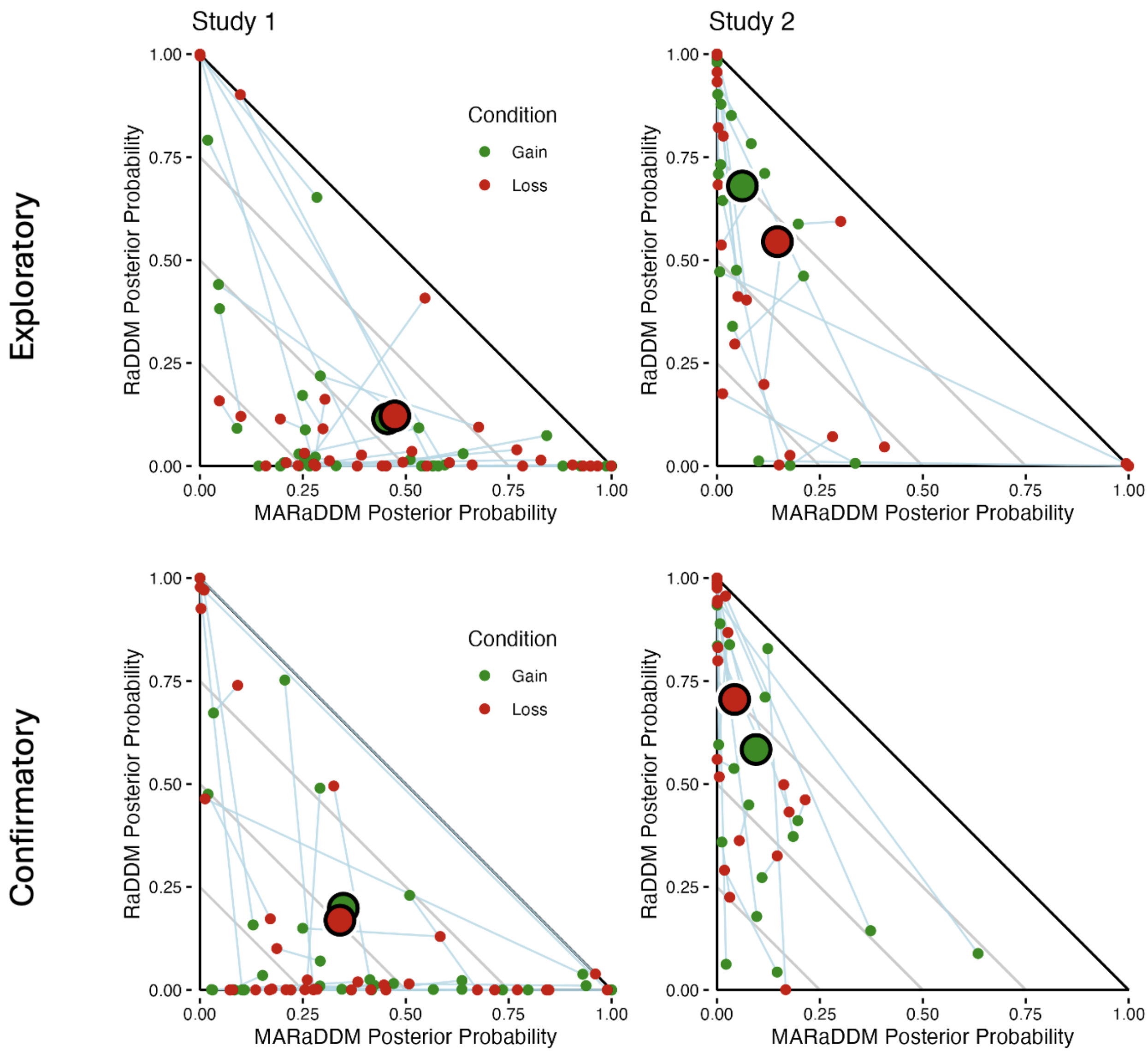
Supplementary Fig. 4. The Effects of the Interaction of Between Attention and Value on Choice. To measure the effect of the value-attention interaction on choice, S. M. Smith and Krajbich (2019) regress choice $\sim \alpha_0 + \alpha_1(V_L - V_R) + \alpha_2(V_L + V_R) + \beta_{Low}(\text{Left Dwell Proportion}|V_L < \text{median}(V_L)) + \beta_{High}(\text{Left Dwell Proportion}|V_L \geq \text{median}(V_L))$. "Left Dwell Proportion" is defined as the proportion of total fixation time in a trial spent fixating on the left option. Here, we repeat this analysis, separately by study and condition, and plot β_{Low} and β_{High} for comparison. Values are range-normalized. Bars denote 95% confidence intervals.



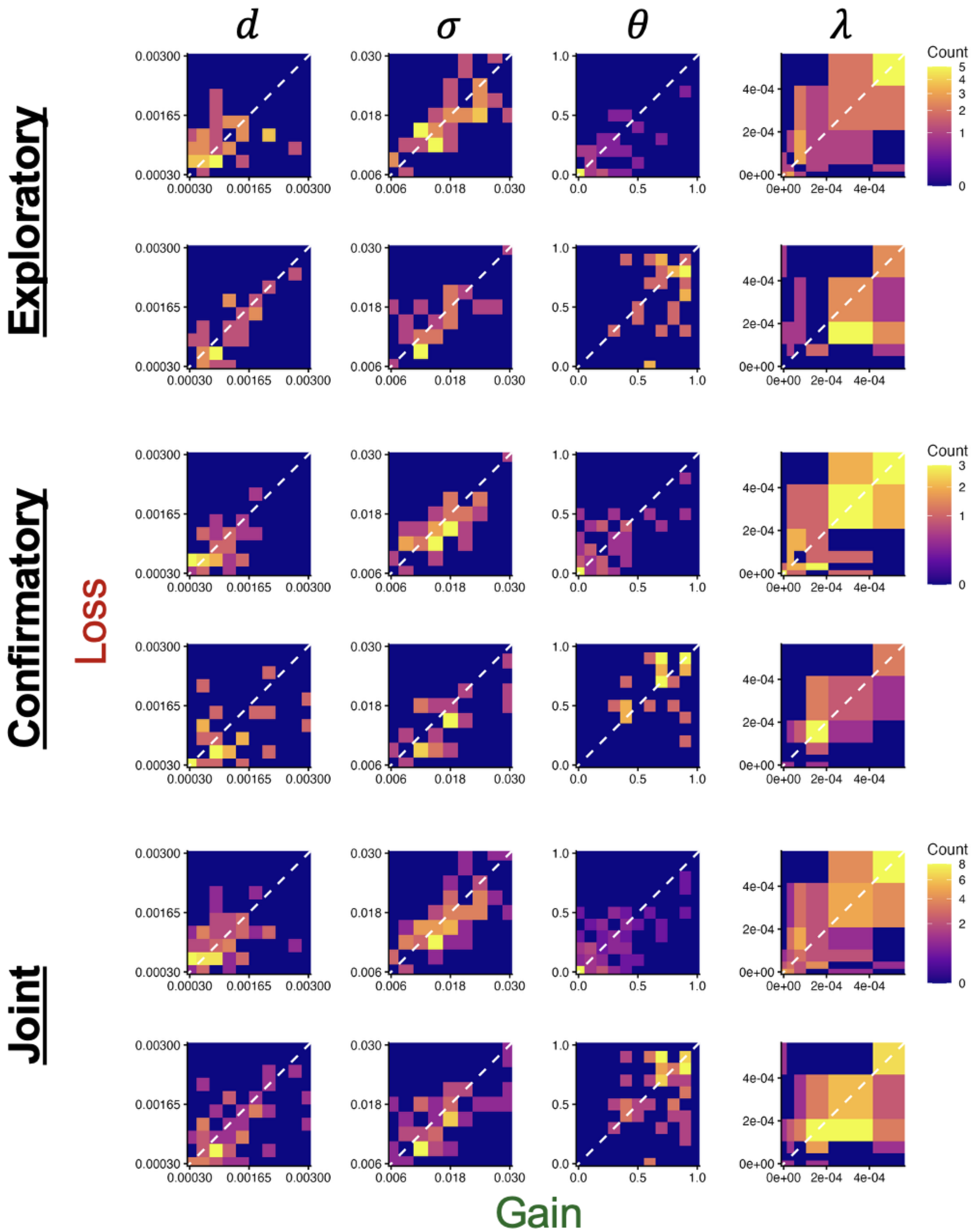
Supplementary Fig. 5. Parameter Grid for Model Fitting. Squares represent every possible combination of (η, θ), given a combination of (d, σ, λ). The Hybrid aDDM nests the DDM, RaDDM, AaDDM, and MARaDDM and is defined on every possible combination of $\eta \in \{0.0000, 0.0002, \ldots, 0.0010\}$ and $\theta \in \{0.0, 0.1, \ldots, 1.0\}$. The MARaDDM has both $\theta < 1$ and $\eta > 0$. The AaDDM fixes $\theta = 1$ and has $\eta > 0$. The RaDDM fixes $\eta = 0$ and has $\theta < 1$. The DDM fixes $\eta = 0$ and $\theta = 1$. $d \in \{0.0003, 0.0006, \ldots, 0.0030\}$, $\sigma \in \{0.006, 0.009, \ldots, 0.030\}$, and $\lambda \in \{0.0, 0.000028, 0.000069, 0.000139, 0.000277, 0.000554\}$ for all models. These λ values correspond to 50% boundary collapse by never, 25s, 10s, 5s, 2.5s, 1.25s, respectively.



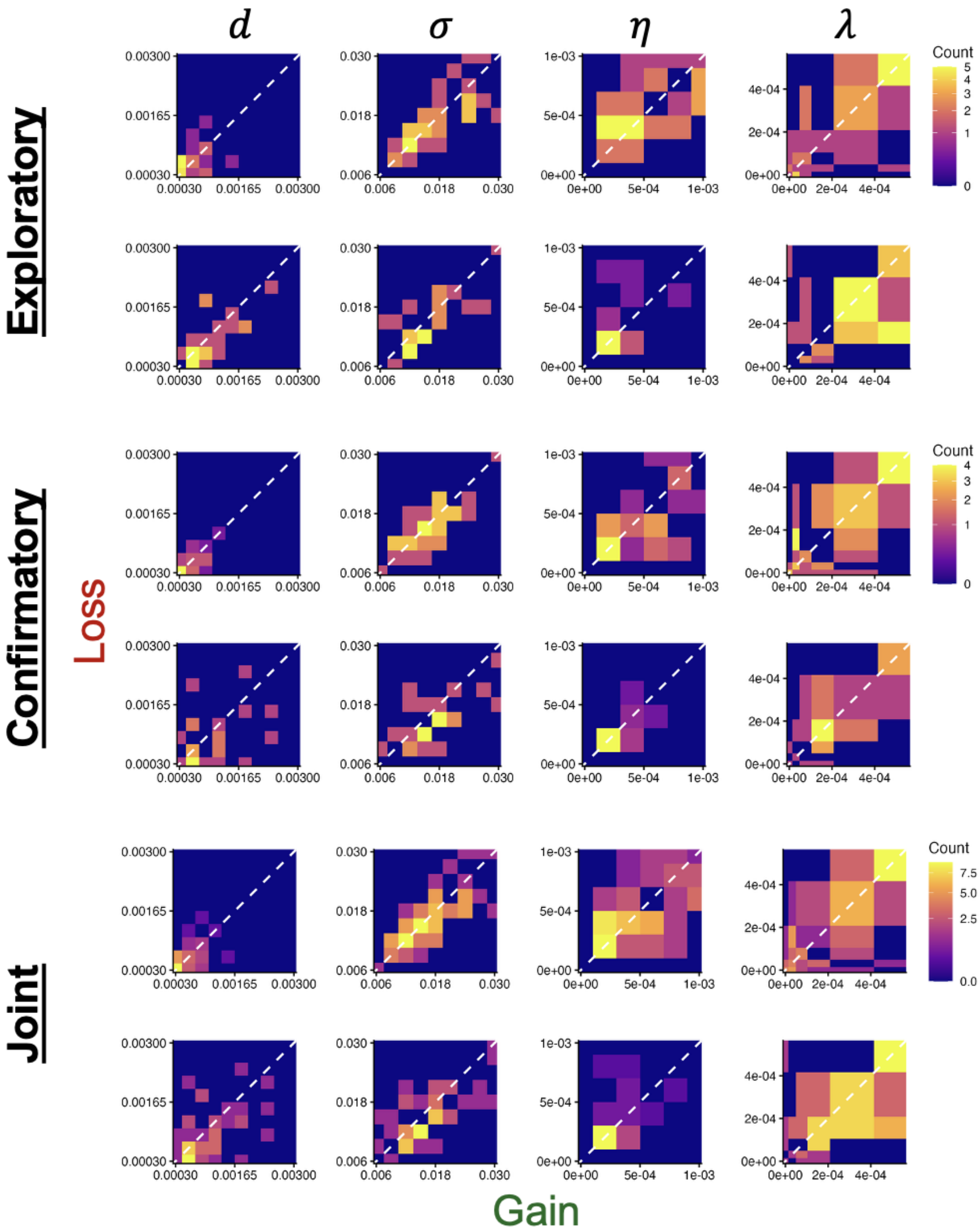
Supplementary Fig. 6. Hybrid aDDM Parameter Recovery. Heatmap of estimated parameter estimates as a function of the true data-generating parameters in a parameter recovery exercise for the Hybrid aDDM. Data was simulated using the Hybrid aDDM with parameters from every combination of: $d \in \{0.0015, 0.003, 0.0045\}$, $\sigma \in \{0.003, 0.007, 0.011\}$, $\theta \in \{0.2, 0.5, 0.8\}$, $\eta \in \{0.0002, 0.0008, 0.0014\}$, $\lambda \in \{0, 0.000028, 0.000139\}$. White lines mark equality between true and recovered values.



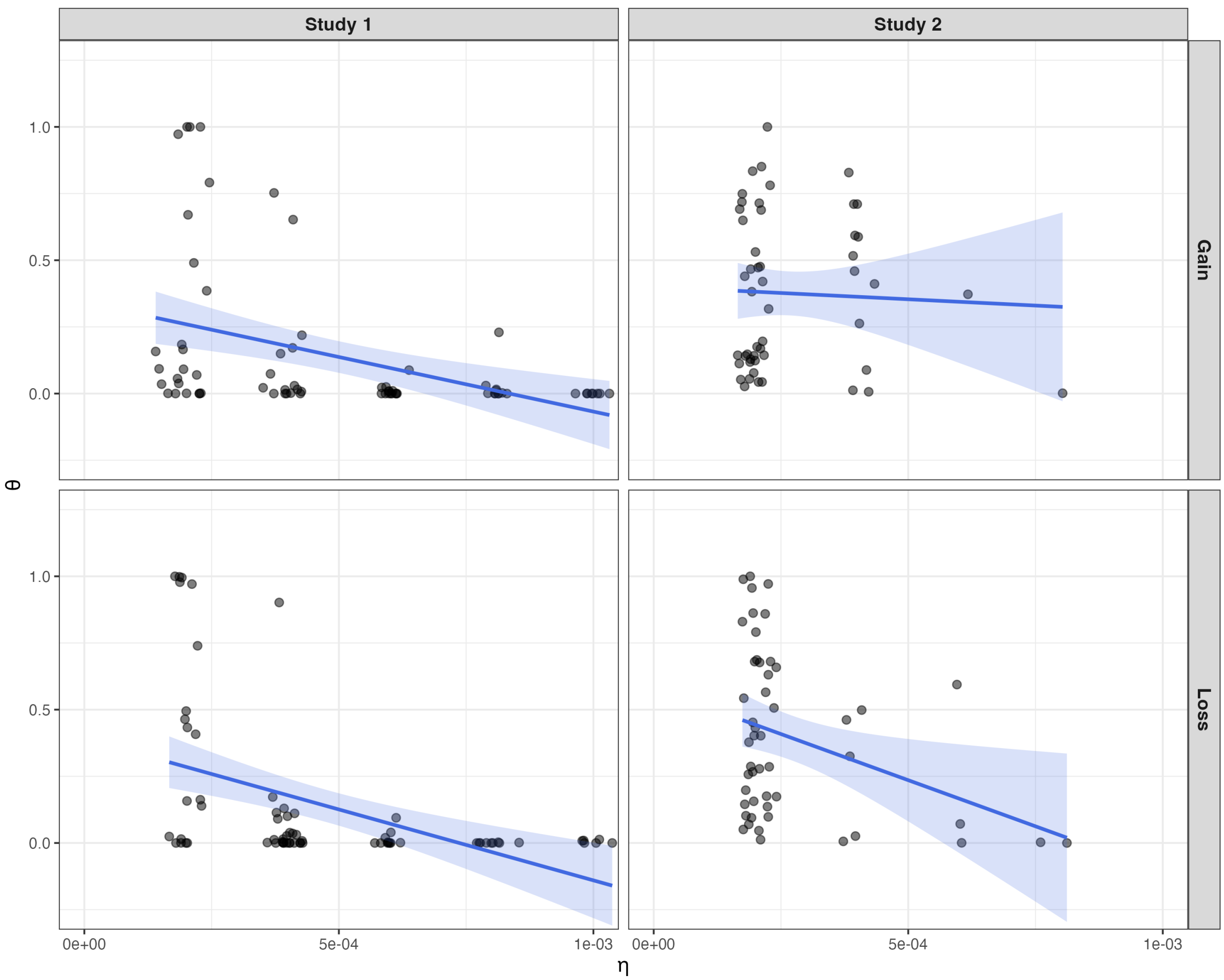
Supplementary Fig. 7. Model Comparison Between RaDDM, AaDDM, and MARaDDM, Plotted as a Probability Simplex, Separately by Dataset. For each participant, the posterior model probability of the RaDDM is plotted as a function of the posterior model probability of the MARaDDM. The posterior model probability of the AaDDM for each individual is therefore 1 minus the sum of their posterior model probabilities for the RaDDM and MARaDDM. Points closer to the origin indicate participants that were best-fit by the AaDDM, points closer to the top indicate participants that were best-fit by the RaDDM, and points closer to the right indicate participants that were best-fit by the MARaDDM. Blue lines connect participants across conditions. Large points indicate the mean across subjects.



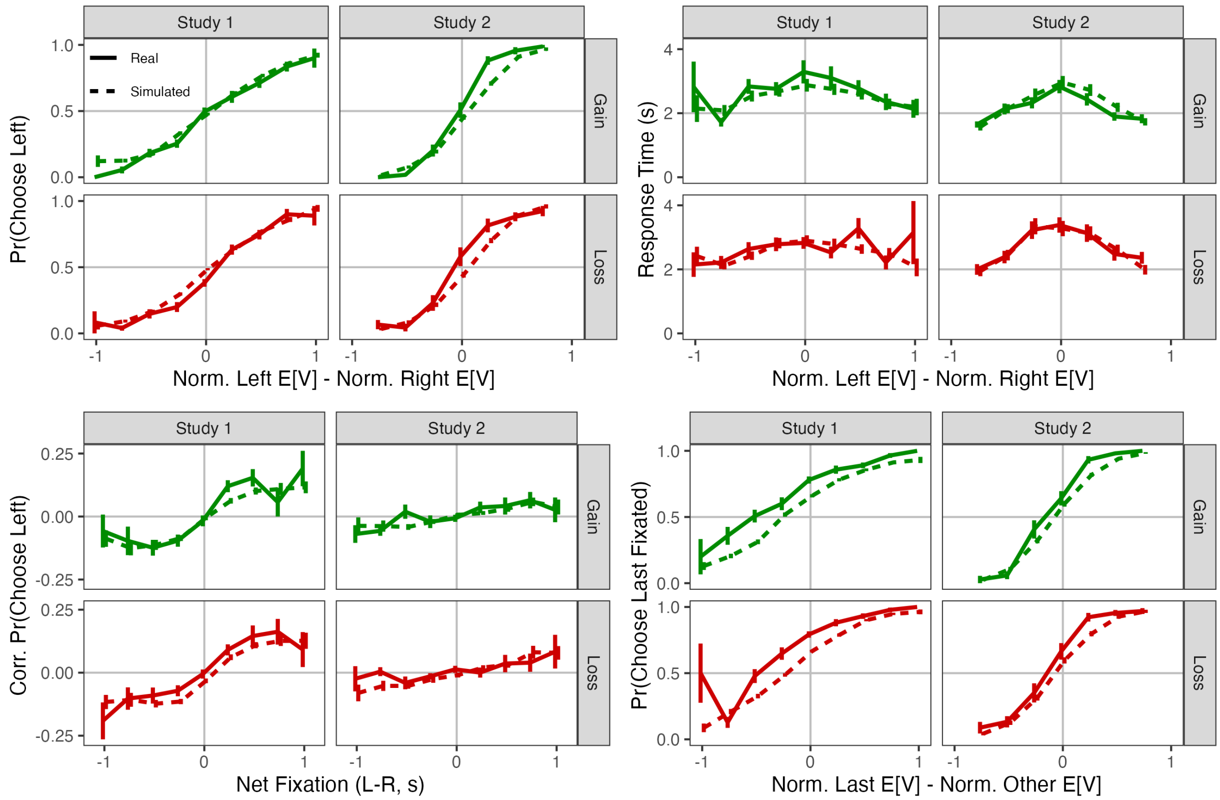
Supplementary Fig. 8. Participant-Level RaDDM Estimates, Split by Dataset. Estimates of the drift rate (d), noise (σ), attentional bias (θ), and exponential barrier collapse (λ) in the loss condition as a function of their counterpart in the gain condition. White lines mark equality across the two conditions.



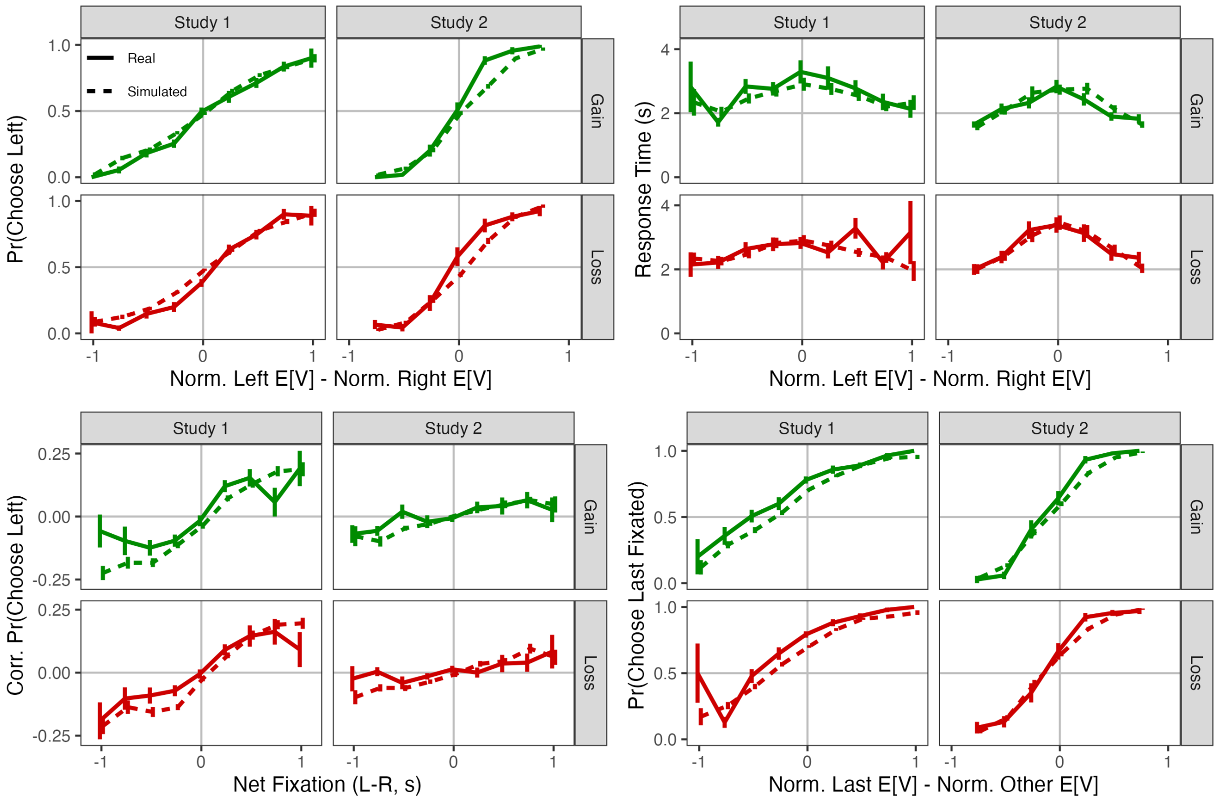
Supplementary Fig. 9. Participant-Level AaDDM Estimates, Split by Dataset. Estimates of the drift rate (d), noise (σ), additive attentional bias (η), and exponential barrier collapse (λ) in the loss condition as a function of their counterpart in the gain condition. White lines mark equality across the two conditions.



Supplementary Fig. 10. Comparing Attentional Biases Across Models. Plots depict fitted θ from the RaDDM as a function of the fitted η from the AaDDM, separately by study (columns) and condition (rows). Note that smaller θ's and larger η's correspond to more attentional bias. Blue lines indicate OLS regression line, with grey 95% confidence intervals. η's are slightly jittered for visual clarity.



Supplementary Fig. 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. 4. (Top Right) Response time as a function of the normalized best minus worst expected value, as in Row 2 of Fig. 4. (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. 6. 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 last fixated option, as in Row 2 of Fig. 6. 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 in joint dataset. 10 simulated datasets per participant. Error bars represent the standard error of the mean across all simulations for all participants.

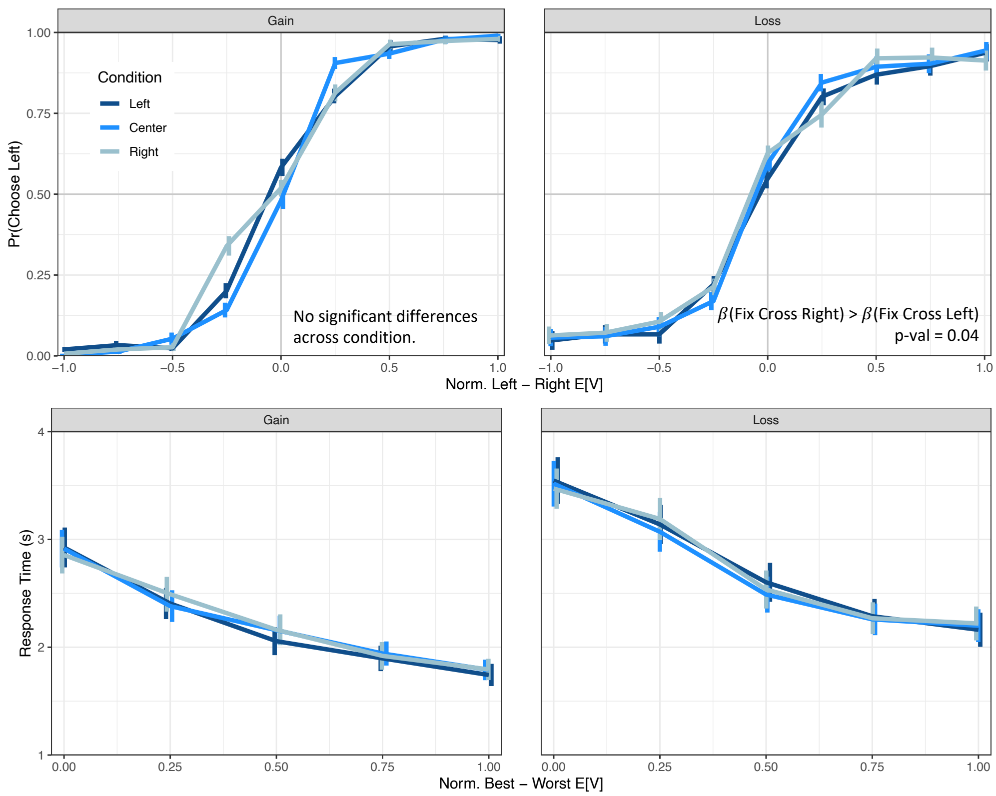


Supplementary Fig. 12. AaDDM Out-of-Sample Predictions. (Top Left) The probability of choosing left as a function of the normalized relative expected value of the left option, as in Row 1 of Fig. 4. (Top Right) Response time as a function of the normalized best minus worst expected value, as in Row 2 of Fig. 4. (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. 6. 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 last fixated option, as in Row 2 of Fig. 6. 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 in joint dataset. 10 simulated datasets per participant. Error bars represent the standard error of the mean across all simulations for all participants.

1 Additional Text

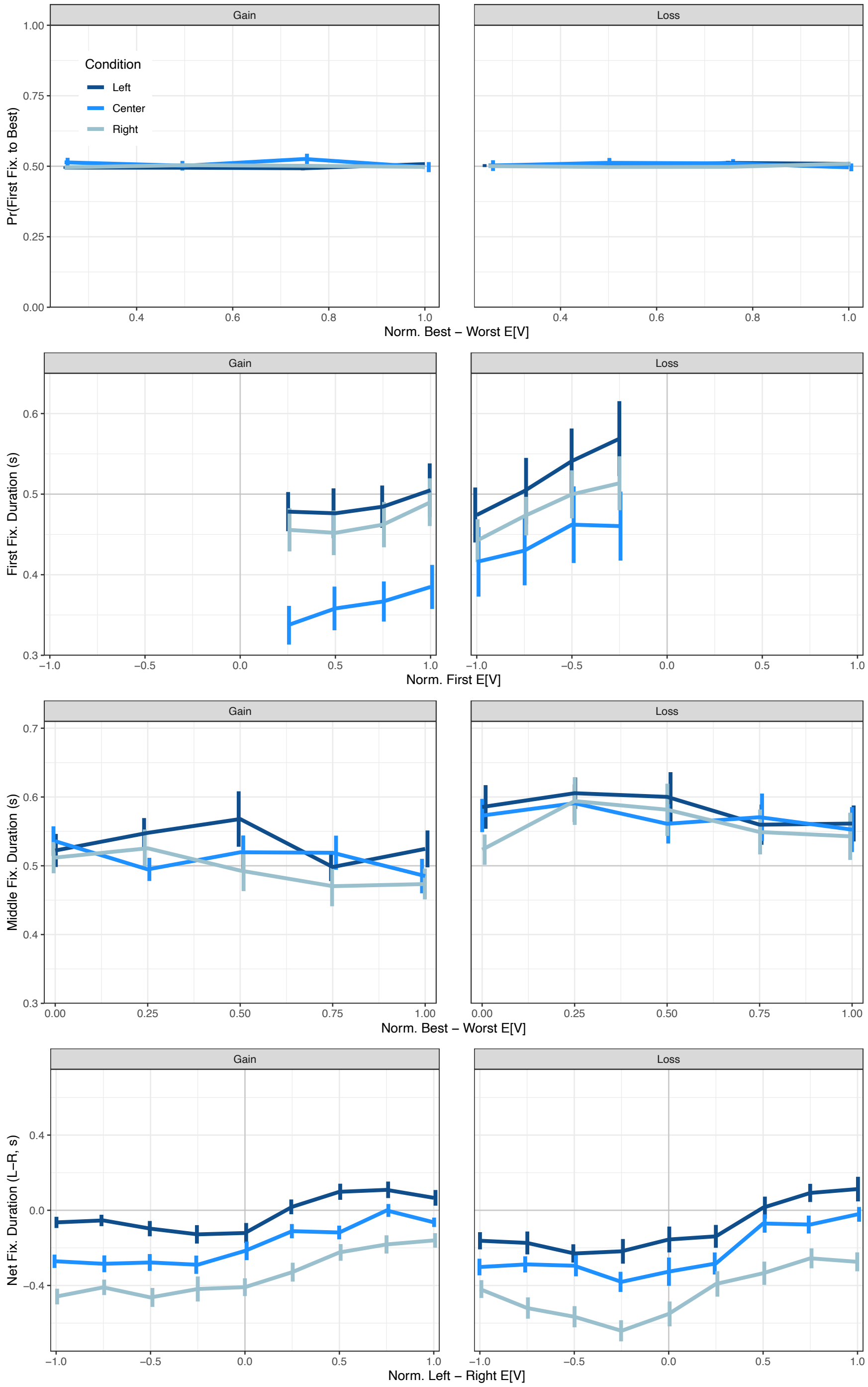
1.1 Attentional Manipulation in Study 2

Using the forced fixation cross to manipulate the location of the first fixation in study 2, we nudged choices away from the target option by a small but significant amount in the loss condition, but not in the gain condition (Fig. S13 top row). RTs did not significantly change in response to attentional manipulations (Fig. S13 bottom row).



Supplementary Fig. 13. 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. Error bars denote standard error of the mean across participants.

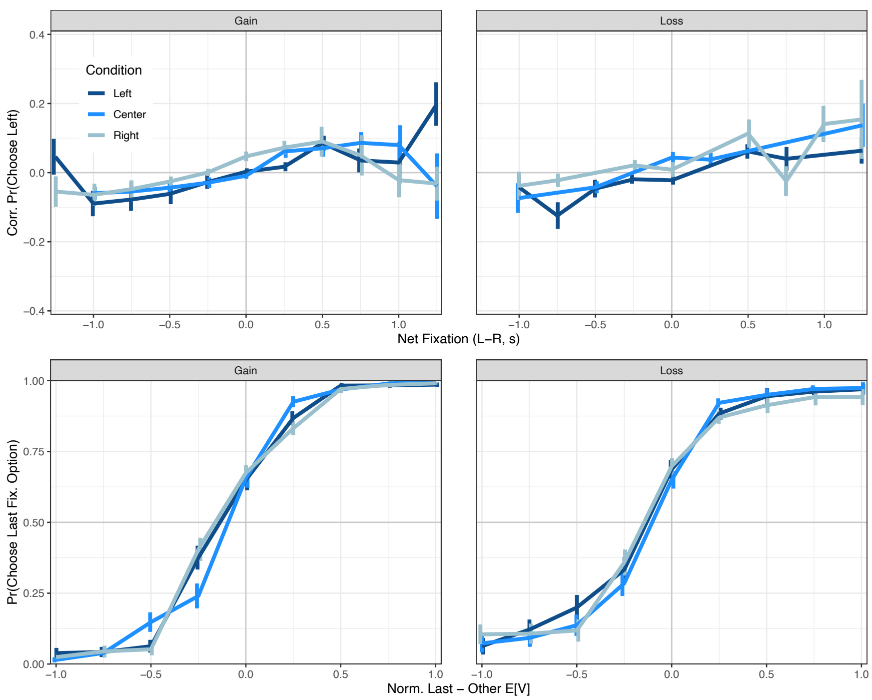
In study 2, we used counterbalancing to ensure that altering the location of the forced fixation cross did not affect the probability of first fixating on the best option (Fig. S14 top row). This attentional manipulation increased first fixation durations by roughly 100 ms on average without altering middle fixation durations (Fig. S14 middle and bottom row). This biased net fixation durations in the direction of the manipulation (Fig. S14 fourth row), partially explaining the right-side attentional favoritism seen in the bottom row of Fig. 5.



Supplementary Fig. 14. 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 expected value of the first seen lottery. 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. Data from the joint dataset.

Manipulating the location of the first fixation using a forced fixation cross at the start of each trial did not affect the magnitude of net fixation bias (Fig. S15 first row). Non-centered fixation crosses reduced the accuracy with which the first and last fixated item was chosen when relative values were close to 0 (Fig. S15 second row). In aversive choices, when the relative value of the first fixated item was equal to 0, the attentional manipulation induced a first fixation bias in the direction of the forced fixation cross (Fig. S15 third row). In choices between gains, this is true for left fixation crosses, but not for right.

This last observation bears on accounts in which the gaze–choice association is purely post-decisional, arising only after a covert commitment has been made (Zylberberg et al., 2026). Because the forced fixation cross fixes the location of the first fixation exogenously, well before a decision could have been reached, a bias induced by that manipulation cannot be attributed to gaze that follows a completed choice.



Supplementary Fig. 15. 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 bottom row depicts the probability of choosing the last fixated option as a function of the normalized relative expected value of the last 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. Data from joint dataset.

Supplementary Tables

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
		Study 1								
Left Chosen	Intercept	-0.17	0.11		-0.40	0.08	*	-0.28	0.07	*
(Logistic)	L - R N. E[V]	2.64	0.13	*	3.05	0.18	*	2.85	0.11	*
(Top)	Loss Condition	-0.16	0.11		0.07	0.12		-0.05	0.08	
	Interaction	0.34	0.16	*	0.14	0.13		0.24	0.10	*
RT (s)	Intercept	2.85	0.31	*	3.56	0.49	*	3.20	0.29	*
(Linear)	B - W N. E[V]	-0.62	0.16	*	-1.26	0.36	*	-0.94	0.20	*
(Middle)	Loss Condition	-0.23	0.24		-0.14	0.37		-0.18	0.22	
	Interaction	0.14	0.15		0.42	0.28		0.28	0.16	
# of Fix.	Intercept	4.16	0.29	*	4.43	0.32	*	4.30	0.22	*
(Linear)	B - W N. E[V]	-0.65	0.14	*	-0.97	0.19	*	-0.81	0.12	*
(Bottom)	Loss Condition	-0.16	0.17		-0.07	0.17		-0.12	0.12	
	Interaction	0.16	0.14		0.12	0.14		0.14	0.09	
		Study 2								
Left Chosen	Intercept	0.13	0.06	*	0.15	0.06	*	0.14	0.04	*
(Logistic)	L - R N. E[V]	7.68	0.49	*	7.02	0.49	*	7.35	0.35	*
(Top)	Loss Condition	0.09	0.09		-0.08	0.10		-0.00	0.07	
	Interaction	-0.56	0.86		0.11	0.66		-0.16	0.56	
RT (s)	Intercept	2.65	0.16	*	2.97	0.29	*	2.81	0.17	*
(Linear)	B - W N. E[V]	-1.49	0.18	*	-1.46	0.21	*	-1.47	0.14	*
(Middle)	Loss Condition	0.72	0.17	*	0.64	0.18	*	0.68	0.12	*
	Interaction	-0.54	0.16	*	-0.32	0.16	*	-0.43	0.11	*
# of Fix.	Intercept	4.34	0.20	*	4.47	0.26	*	4.41	0.16	*
(Linear)	B - W N. E[V]	-2.03	0.22	*	-2.02	0.22	*	-2.03	0.15	*
(Bottom)	Loss Condition	0.59	0.17	*	0.34	0.21		0.47	0.13	*
	Interaction	-0.54	0.18	*	-0.22	0.20		-0.38	0.13	*

* indicates significance in all data sets at the 95% confidence level.
"N. E[V]": Range-normalized expected value. "B - W": Best - worst.

Supplementary Table 1. Regressions associated with the basic psychometric 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		0.05	0.07		-0.02	0.05	
(Logistic)	B - W N. E[V]	0.22	0.12		-0.07	0.13		0.08	0.09	
(Row 1)	Loss Condition	0.11	0.10		0.02	0.09		0.07	0.07	
	Interaction	-0.32	0.18		-0.06	0.17		-0.19	0.12	
Mid. Fix. Dur.	Intercept	0.71	0.04	*	0.81	0.05	*	0.76	0.03	*
(Linear)	B - W N. E[V]	-0.04	0.02	*	-0.10	0.03	*	-0.07	0.02	*
(Row 3)	Loss Condition	-0.01	0.04		0.00	0.04		-0.00	0.03	
	Interaction	0.00	0.02		0.05	0.04		0.02	0.03	
1st Fix. Dur.	Intercept	0.56	0.05	*	0.65	0.04	*	0.60	0.03	*
(Linear)	First N. E[V]	0.00	0.01		-0.03	0.01		-0.01	0.01	
(Row 4)	Loss Condition	-0.02	0.04		0.02	0.04		0.00	0.03	
	Interaction	0.00	0.01		0.04	0.02		0.02	0.01	
Net Fix. Dur.	Intercept	0.04	0.03		0.03	0.04		0.03	0.02	
(Linear)	L - R N. E[V]	0.18	0.02	*	0.15	0.03	*	0.16	0.02	*
(Row 5)	Loss Condition	-0.06	0.03	*	0.05	0.04		-0.01	0.03	
	Interaction	0.02	0.03		0.15	0.07	*	0.08	0.04	*
					Study 2					
1st Fix. Best	Intercept	-0.02	0.10		0.05	0.10		0.02	0.07	
(Logistic)	B - W N. E[V]	0.04	0.19		-0.07	0.19		-0.01	0.13	
(Row 1)	Loss Condition	0.05	0.14		-0.09	0.14		-0.02	0.10	
	Interaction	-0.10	0.27		0.19	0.26		0.05	0.19	
Mid. Fix. Dur.	Intercept	0.52	0.02	*	0.54	0.03	*	0.53	0.02	*
(Linear)	B - W N. E[V]	-0.08	0.03	*	0.00	0.03		-0.04	0.02	*
(Row 3)	Loss Condition	0.03	0.02		0.07	0.02	*	0.05	0.01	*
	Interaction	0.04	0.03		-0.02	0.04		0.01	0.02	
1st Fix. Dur.	Intercept	0.43	0.02	*	0.47	0.04	*	0.45	0.02	*
(Linear)	First N. E[V]	0.02	0.01		0.02	0.01		0.02	0.01	*
(Row 4)	Loss Condition	0.05	0.01	*	0.08	0.03	*	0.07	0.01	*
	Interaction	-0.00	0.02		0.00	0.02		0.00	0.01	
Net Fix. Dur.	Intercept	-0.16	0.04	*	-0.20	0.04	*	-0.18	0.02	*
(Linear)	L - R N. E[V]	0.19	0.03	*	0.18	0.03	*	0.18	0.02	*
(Row 5)	Loss Condition	-0.05	0.03		-0.09	0.04	*	-0.07	0.03	*
	Interaction	0.02	0.04		0.02	0.04		0.02	0.03	

* indicates significance in all data sets at the 95% confidence level.
"N. E[V]": Range-normalized expected value. "B - W": Best - worst.

Supplementary Table 2. Regressions associated with the fixation process results in Fig. 5.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
		Study 1								
1st Fix. L	Intercept	1.23	0.28	*	1.29	0.35	*	1.26	0.22	*
(Logistic)	L - R N. E[V]	0.07	0.10		0.05	0.08		0.07	0.06	
(Top)	Loss Condition	0.32	0.14	*	0.01	0.16		0.17	0.11	
	Interaction	-0.16	0.12		0.05	0.11		-0.05	0.08	
2nd Fix. Dur.	Intercept	0.66	0.05	*	0.73	0.05	*	0.69	0.04	*
(Linear)	B - W N. E[V]	-0.05	0.01	*	-0.08	0.02	*	-0.07	0.01	*
(Middle)	Loss Condition	-0.02	0.04		0.01	0.03		-0.01	0.02	
	Interaction	0.02	0.02		0.06	0.03		0.04	0.02	*
3rd Fix. Dur.	Intercept	0.58	0.05	*	0.66	0.05	*	0.62	0.03	*
(Linear)	B - W N. E[V]	-0.08	0.02	*	-0.10	0.03	*	-0.09	0.02	*
(Bottom)	Loss Condition	-0.00	0.04		0.06	0.04		0.03	0.03	
	Interaction	0.01	0.03		-0.01	0.04		-0.00	0.03	
		Study 2								
1st Fix. L	Intercept	0.22	0.07	*	0.24	0.06	*	0.23	0.04	*
(Logistic)	L - R N. E[V]	0.01	0.06		0.02	0.06		0.02	0.05	
(Top)	Loss Condition	-0.03	0.05		0.00	0.05		-0.01	0.04	
	Interaction	-0.01	0.09		0.02	0.09		0.01	0.06	
2nd Fix. Dur.	Intercept	0.52	0.03	*	0.61	0.07	*	0.57	0.04	*
(Linear)	B - W N. E[V]	-0.05	0.03		-0.10	0.05		-0.07	0.03	*
(Middle)	Loss Condition	0.05	0.02	*	0.13	0.04	*	0.09	0.02	*
	Interaction	-0.00	0.04		-0.06	0.05		-0.03	0.03	
3rd Fix. Dur.	Intercept	0.51	0.02	*	0.50	0.03	*	0.50	0.02	*
(Linear)	B - W N. E[V]	-0.19	0.03	*	-0.09	0.04	*	-0.14	0.03	*
(Bottom)	Loss Condition	0.04	0.02		0.09	0.03	*	0.07	0.02	*
	Interaction	0.04	0.04		0.00	0.06		0.02	0.04	

* indicates significance in all data sets at the 95% confidence level.
"N. E[V]": Range-normalized expected value. "B - W": Best - worst.

Supplementary Table 3. Regressions associated with the additional fixation properties results in Fig. 1.

		Exploratory			Confirmatory			Joint		
Dept. Var.	Indept. Var.	Est.	SE		Est.	SE		Est.	SE	
					Study 1					
Corr. L Chosen	Intercept	0.01	0.01		-0.00	0.01		0.00	0.00	
(Linear)	Net Fix. Left	0.37	0.05	*	0.25	0.04	*	0.31	0.04	*
(Top)	Loss Condition	0.00	0.01		0.00	0.01		0.00	0.00	
	Interaction	0.02	0.04		-0.02	0.03		-0.00	0.03	
Last Fix. Chosen	Intercept	1.27	0.17	*	1.54	0.17	*	1.40	0.12	*
(Logistic)	Last - Other N. E[V]	2.55	0.14	*	2.83	0.17	*	2.69	0.11	*
(Middle)	Loss Condition	0.05	0.08		-0.03	0.08		0.01	0.06	
	Interaction	0.25	0.19		0.21	0.16		0.23	0.13	
					Study 2					
Corr. L Chosen	Intercept	0.01	0.00	*	0.01	0.00		0.01	0.00	*
(Linear)	Net Fix. Left	0.09	0.02	*	0.06	0.01	*	0.07	0.01	*
(Top)	Loss Condition	-0.00	0.01		0.00	0.01		0.00	0.00	
	Interaction	-0.02	0.02		-0.02	0.01		-0.02	0.01	
Last Fix. Chosen	Intercept	0.60	0.14	*	0.74	0.11	*	0.67	0.09	*
(Logistic)	Last - Other N. E[V]	7.73	0.52	*	7.00	0.51	*	7.35	0.36	*
(Middle)	Loss Condition	0.11	0.13		-0.03	0.10		0.03	0.08	
	Interaction	-0.78	0.82		0.14	0.65		-0.27	0.53	

* indicates significance in all data sets at the 95% confidence level.
"N. E[V]": Range-normalized expected value. "B - W": Best - worst.

Supplementary Table 4. Regressions associated with the attentional choice biases results in Fig. 6.

Loss Condition

Dept. Var.	Indept. Var.	RaDDM Est.	RaDDM SE		AaDDM Est.	AaDDM SE		MARaDDM Est.	MARaDDM SE	
Study 1	β_0 Intercept	0.87	0.07	*	0.85	0.08	*	0.86	0.08	*
$log(RT)$	β_1 Abs. Net N. Value	-0.40	0.03	*	-0.41	0.04	*	-0.38	0.04	*
(Linear)	β_2 Overall N. Value	-0.02	0.01	*	-0.01	0.01		-0.02	0.01	*
Study 2	β_0 Intercept	0.56	0.11	*	1.16	0.09	*	1.21	0.09	*
$log(RT)$	β_1 Abs. Net N. Value	-0.79	0.06	*	-0.95	0.09	*	-0.96	0.09	*
(Linear)	β_2 Overall N. Value	-0.20	0.08	*	-0.01	0.01		-0.04	0.01	*

Gain Condition

Dept. Var.	Indept. Var.	RaDDM Est.	RaDDM SE		AaDDM Est.	AaDDM SE		MARaDDM Est.	MARaDDM SE	
Study 1	β_0 Intercept	1.04	0.10	*	0.89	0.11	*	0.91	0.11	*
$log(RT)$	β_1 Abs. Net N. Value	-0.33	0.03	*	-0.35	0.03	*	-0.33	0.03	*
(Linear)	β_2 Overall N. Value	-0.03	0.01	*	-0.01	0.01		-0.01	0.01	
Study 2	β_0 Intercept	1.20	0.09	*	1.16	0.09	*	1.18	0.08	*
$log(RT)$	β_1 Abs. Net N. Value	-1.19	0.08	*	-1.22	0.07	*	-1.19	0.06	*
(Linear)	β_2 Overall N. Value	-0.04	0.01	*	0.01	0.01		-0.02	0.01	

* indicates significance in all data sets at the 95% confidence level.
"N.": Normalized. "Abs.": Absolute.

Supplementary Table 5. Model Comparison Regression Test in Simulated Data Using RaDDM, AaDDM, and MARaDDM.

We simulated data using parameter estimates from our subjects in the Exploratory dataset. For each subject, we simulate 10 datasets. We then use Eq. 1 to run the same regression test used in Table 1. These results confirm that the relationship between response time and overall value can be used to distinguish the models in our data. The RaDDM predicts a significantly negative β_2. The AaDDM predicts an insignificant β_2. The MARaDDM sometimes predicts a negative β_2 and other times predicts an insignificant β_2, depending on the degree of multiplicative versus additive attentional discounting.