Attention in Aversive Choice Still Biases Choices Towards the Attended Option

Brenden Eum[1,3], Stephen Gonzalez[2,4], and Antonio Rangel[1,5]

[1]California Institute of Technology, Humanities and Social Sciences
[2]Stanford University, Graduate School of Education
[3]beum@caltech.edu; Corresponding Author
[4]stephengonz151@gmail.com
[5]rangel@hss.caltech.edu

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Abstract

Simple choices between positively-valued options are common in our daily lives and are susceptible to robust attentional choice biases. However, we also encounter choices between negatively-valued options ("aversive choice"). Based on previous evidence and the predictions of attentional choice process models, we hypothesized that attentional choice biases would reverse as people switch from choices between gains to aversive choices. However, in this paper, we find no evidence for a reversal in attentional choice biases. To explain this, we propose a few changes to the Attentional Drift-Diffusion-Model regarding value encoding and the role of attention in the decision process. These results suggest that even in aversive choices, decision-makers are still susceptible to the same attentional manipulations that work in gains.

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

Introduction

Everyday, we have to make decisions about things that we want. What do I want to eat for dinner? What product do I want to buy? What show do I want to watch? During these decisions, previous studies have established the existence of robust attentional choice biases that pull choices towards attended options (Smith & Krajbich, 2018; Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Eum, Dolbier, & Rangel, 2023). For instance, people are more likely to choose the option they attended to more and that they last fixated on.

However, we also frequently encounter choices where the outcomes are not pleasant. Which bill should I pay off first? Do I really need to repair the car? Must I vote for one of these two candidates? In these aversive scenarios, it's not clear what the role of attention is in the decision-making process.

Previous work has demonstrated that manipulating attention in favor of an option biases choices towards that option (Tavares, Perona, & Rangel, 2017), and that this effect reverses in aversive choices with forced fixations and fixed response times (Armel, Beaumel, & Rangel, 2008). However, decision-makers are often free to determine their own fixation process and make a decision when they're ready. Therefore, it's not clear if this attentional effect extends to aversive decisions with free-look and free response time.

In this paper, we apply a variation of the Drift-Diffusion-Model (Ratcliff & McKoon, 2008) called the Attentional Drift-Diffusion-Model (aDDM) to unravel the role of attention in aversive choice. The aDDM provides a framework to investigate the role of attention during the decision-making process, while taking into consideration other factors like noise and response caution (Krajbich et al., 2010). The attentional parameter in the aDDM yields a quantitative measurement of the effect of attention on the decision process.

Based on previous estimates of the attentional parameter in the aDDM (Bhatnagar & Orquin, 2022), we hypothesized that in simple aversive choices, attention to an aversive option should drive choices towards the alternative. Behaviorally, this would imply that decision-makers should be less likely to choose the option they attended to longer and that they last fixated on.

We test these hypotheses in two studies involving simple, risky choices. In both studies, participants made a series of binary choices between two lotteries, separated into blocks based on 2 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. Study 1 represented lotteries with colored dots in a circle to represent probabilities, and study 2 presented information about the lotteries numerically.

To preview the results, we find evidence that contradicts our initial hypotheses. In aversive choices, just as in gain choices, decision-makers are more likely to choose the option they attended to more and that they last fixated on. We find that this behavior is still consistent with a few different forms of the aDDM: one where attentional effects are value-independent (Cavanagh, Wiecki, Kochar, & Frank, 2014), and another where value signals are context dependent and consider the goal (Sepulveda et al., 2020).

Results

Paradigm

To investigate the role of attention in the aversive choice process, we ran two studies involving binary risky choices (see Fig. 1). Both studies were split equally into gain or loss conditions where participants either chose from positive- or negative-outcome lotteries.

In study 1 (n=72), participants began the trial with a forced fixation cross in the center of the screen for 1 s. In the gain condition, subjects 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. Subjects were given free response time to select the lottery they prefer, and after selecting, were given feedback about the choice they made 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. For more details, see the *Methods*.

One potential issue with presenting lotteries as perceptual stimuli is that participants can easily switch between 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 red 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 this switching was not happening, we ran a second study with numerical representations of the lotteries.

In study 2 (n=50), participants began the trial by fixating for 1 s on a fixation cross that can appear on the left, middle, or right side of the screen. In the gain condition, participants were presented with two lotteries in green. Lotteries were comprised of a positive outcome and probability q of earning that outcome, with an implicit \$0 outcome with $1 - q$. Differences in expected value of the lotteries were bounded between \$0 and ±\$4, depending on condition. Participants could look freely and had free response time. Upon making a decision, they received feedback about their choice for 1 s. In the loss condition, trials were similar, but lottery were presented in red and their outcomes were negative. See the *Methods* for more details.

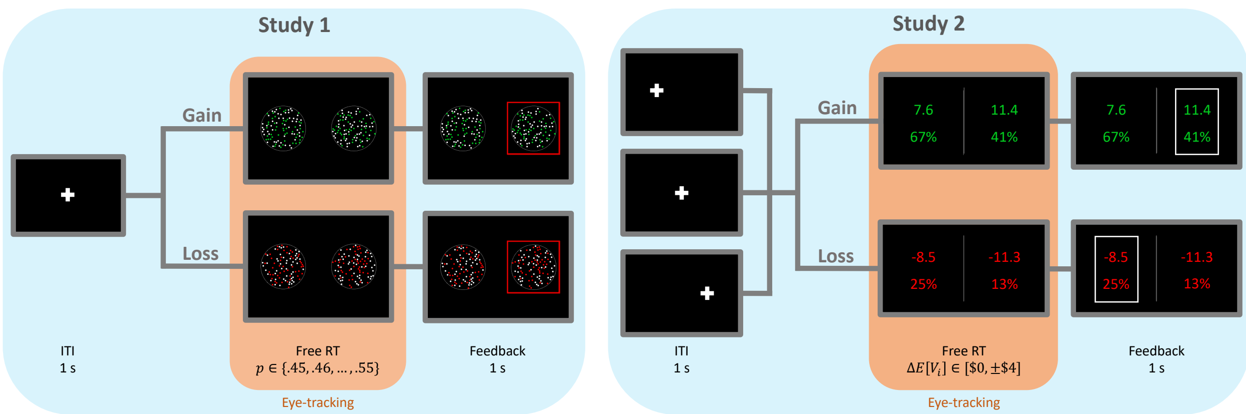

Fig. 1. Tasks. Trials begin with a forced fixation cross for 1 s. In study 1, the fixation cross is fixed in the center; but in study 2, it varies evenly between the left, center, and right side of the screen. Participants then make a binary choice between two lotteries on the left and right side of the screen. 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 and we are recording 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 $p \in \{45, ..., 55\}$, 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 $[\$0, \pm\$4]$, depending on condition.

Basic Psychometrics

The top row of Fig. 2 depicts a psychometric curve, separately for each experimental condition (color), study (line type), and dataset (column). See the *Methods* for an explanation of the different datasets. Table 1 in the Supplementary contains associated statistical analysis. Choices were more sensitive to relative expected value ($\Delta E[V]$) in study 2 than in study 1 (study 1: 95% CI = [2.39, 2.91]; study 2: 95% CI = [5.99, 8.22]). 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 (95% CI = [0.03, 0.68]), but this disappears in study 2 (95% CI = [-2.24, 1.17]). The middle row of Fig. 2 depicts RTs as a function of normalized choice difficulty. In both studies, as in previous literature, we replicated increasing response times in choice difficulty (study 1: 95% CI = [-0.91, -0.33]; study 2: 95% CI = [-1.28, -0.77]). In study 1, RTs were not significantly different in the loss condition (95% CI = [-0.70, 0.25]), regardless of choice difficulty (95% CI = [-0.15, 0.42]). In study 2, RTs were on average 0.7 s slower in the loss condition (95% CI = [0.37, 1.03]). This difference shrinks at a small but significant rate as choices become easier (95% CI = [-0.61, -0.16]). 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 many participants self-reported after the experiment concluded. The bottom row of Fig. 2 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 (95% CI = [-0.49, 0.16]), while they increased by roughly 0.6 on average in the loss condition in study 2 (95% CI = [0.25, 0.89]).

Using the forced fixation cross to manipulate the location of the first fixation in study 2, we nudged choices towards target options by a small but significant amount (Fig. S1 top row) without significant changes in RTs (Fig. S1 bottom row).

Overall, there seemed to be a negligible difference in the quality of choices between the gain and loss conditions in both studies, but significant differences in the speed of the choice processes that depended on the format of the stimuli.

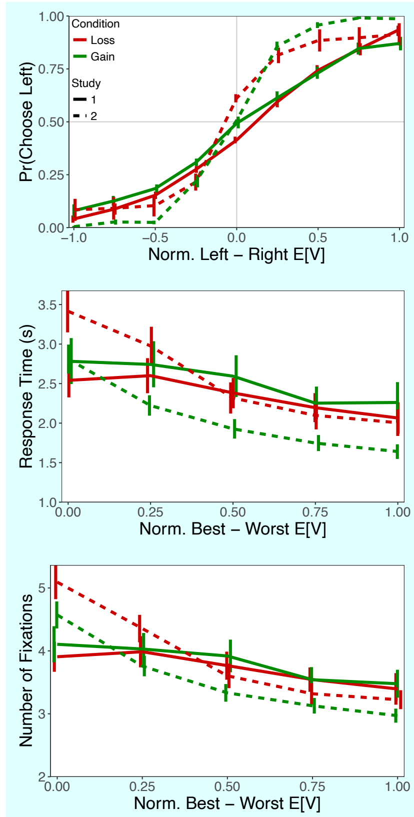

Fig. 2. Basic Psychometrics. The top row depicts the probability of choosing the left item as a function of the normalised expected value difference between the left and right lotteries ("relative value"). Expected values were normalized by dividing by the maximum magnitude of the difference. The middle row depicts response time as a function of normalized choice difficulty, measured by the expected value difference between the best and worst lottery then divided by the maximum magnitude of the difference. The bottom row depicts the number of fixations as a function of normalized choice difficulty. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

Fixation Process

Fig. 3 and Table 2 explore how the fixation process differs between the gain and loss condition in studies 1 and 2.

The first row of Fig. 3 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 (study 1: 95% CI = [-0.22, 0.03]; study 2: 95% CI = [-0.18, 0.14]), suggesting proper counterbalancing of the location of stimuli.

The second row of Fig. 3 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: $p = .01$; Last, Gain-Loss: $p < 0.001$), though only by 30 to 50 ms on average (i.e. less than half a typical blink).

The third row of Fig. 3 depicts mean middle fixation duration as a function of choice difficulty.

In both studies, middle fixation durations were not significantly sensitive to condition (study 1: 95% CI = [-0.08, 0.06]; study 2: 95% CI = [-0.01, 0.08]) and slightly increased in choice difficulty (study 1: 95% CI = [-0.08, -0.01]; study 2: 95% CI = [-0.10, -0.03]).

The fourth row of Fig. 3 depicts mean first fixation duration as a function of choice difficulty. In both studies, first fixation durations were not sensitive to choice difficulty (study 1: 95% CI = [-0.01, 0.05]; study 2: 95% CI = [-0.01, 0.05]). In study 2, first fixation durations were slightly longer in the loss condition (95% CI = [0.01, 0.07]), but this pattern was not present in study 1 (95% CI = [-0.13, 0.05]).

The fifth row of Fig. 3 depicts net fixation duration to the left lottery as a function of $\Delta E[V]$. In both studies, the relationship exhibits a significant positive relationship (study 1: 95% CI = [0.13, 0.22]; study 2: 95% CI = [0.09, 0.19]). In study 1, 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 2 (study 1: 95% CI = [-0.12, -0.01]; study 2: 95% CI = [-0.11, 0.01]). When lotteries had equal expected value, they were fixated about the same amount in study 1 (95% CI = [-0.03, 0.10]), but the right-side lottery received significantly more attention in study 2 (95% CI = [-0.24, -0.09]). This right-side attentional favoritism was not related to first fixation location or differences in the second or third fixations (Fig. S4), but was partially driven by the location of the fixation cross (Fig. S2 bottom row).

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. S2 top row). However, this attentional manipulation did increase first fixation durations by roughly 100 ms on average, without altering middle fixation durations (Fig. S2 middle and bottom row). This biased net fixation durations in the direction of the manipulation (Fig. S2 fourth row), partially explaining the right-side attentional favoritism seen in the bottom row of Fig. 3.

Overall, while there were some statistically significant differences in fixation patterns between the gain and loss conditions, these differences were very small and unlikely to result in meaningful changes to the choice process.

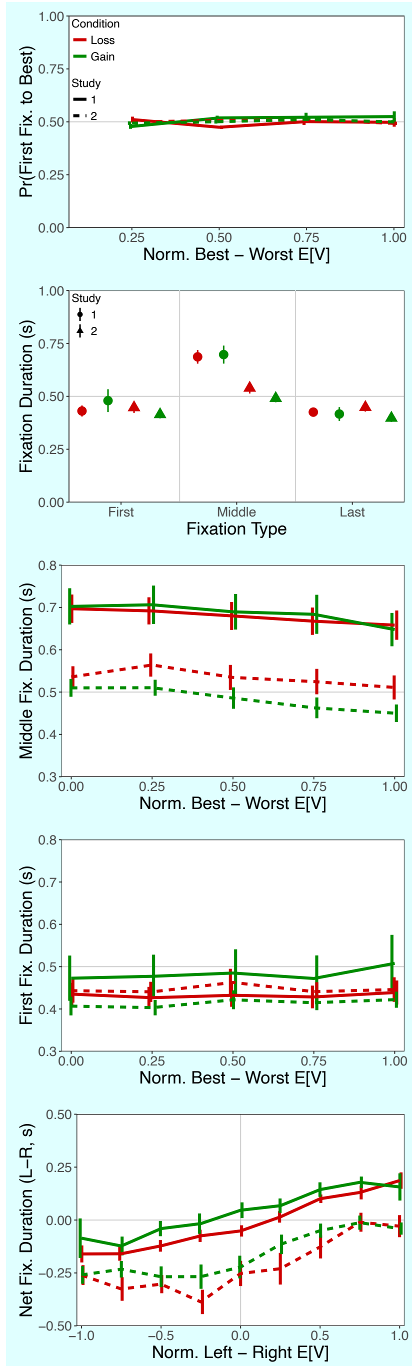

Fig. 3. Fixation Process. The first row depicts the probability of first fixating on the best lottery as a function of normalized choice difficulty. The best lottery is determined by expected value, ignoring risk preferences. The second row depicts fixation durations as a function of fixation type. The third row depicts middle fixation durations as a function of normalized choice difficulty. The fourth row depicts first fixation durations as a function of normalized choice difficulty. The fifth row depicts net fixation duration to the left lottery as a function of its normalized relative expected value. Columns indicate which data set generated the figures. Error bars show the standard error of the mean across participants.

aDDM-Based Hypotheses

In previous studies, the aDDM has provided a robust framework for quantitatively investigating the relationship between fixations, choices, and RTs. The model assumes a noisy sampling process, where evidence is integrated over time until enough is accumulated to make a decision with a certain level of caution. The evidence sampled at every point in time depends on two key components: subjective discriminability of the two options and where the agent is fixating. In the case of lottery choice, we assume evidence is a comparison of the E[V] of the lotteries, where the E[V] of the nonfixated lottery is biased by the attentional parameter in the model. Typically, estimates of the attentional parameter fall between [0,1], suggesting attentional "discounting" of the nonfixated option (Bhatnagar & Orquin, 2022). This interpretation of the attentional parameter is consistent with existing Bayesian models of information sampling (Jang, Sharma, & Drugowitsch, 2021; Callaway, Rangel, & Griffiths, 2021).

Attentional discounting of the nonfixated option in the aDDM allows the model to quantitatively predict robust attentional choice biases in observed behavior (Krajbich et al., 2010; Smith & Krajbich, 2018; Tavares et al., 2017). There are three attentional choice biases that spotlight the relationship between visual attention and choice: (1) net fixation bias, (2) last fixation bias, (3) and first fixation bias. With attentional discounting in choices between gains, the accumulator is biased towards the fixated option (see Fig. 4 "Gain"). Therefore, the aDDM would predict: (1) choices are biased towards the option that received more attention; (2) choices are biased towards the last fixated option; and (3) choices are biased towards the first fixated option. I know this isn't the correct definition of first fixation bias according to previous literature, but because of the fixation cross manipulations in study 2, I want to reframe this bias in a way that better shows what's affected. This means the first fixation bias figure is going to look like the last fixation bias figure, which has also changed in this paper.

However, with attentional discounting in aversive choice, the accumulator is biased towards the *nonfixated* option. This is because discounted negative values are pulled closer to 0 (see Fig. 4 "Loss"). Therefore, the aDDM would predict reversals of attentional choice biases: (1) choices are biased away from the option that received more attention; (2) choices are biased away from the last fixated option; and (3) choices are biased away from the first fixated option. Armel et al. (2008) found evidence for these reversals in binary food choices with forced fixations and response times. In their paradigm, aversive food items were sequentially presented for pre-determined durations, after which participants made a forced choice. However, it's possible that forced sequential presentation of the aversive items altered the choice process in a manner that encourages these reversals. For instance, it encourages separate evaluations of the options and discourages their comparison (Eum et al., 2023; Basu & Savani, 2017, 2019). In turn, this could result in re-framing of the evidence (or a lack thereof).

Here, we ask if these attentional choice bias reversals in aversive choice still persist in simple choices when decision-makers are free to look at either stimuli and respond when ready. We hypothesized that in the loss condition, estimates of the attentional parameter would remain between [0,1], and therefore we would observe attentional choice bias reversals when behavior is compared to the gain condition.

Attentional Choice Biases

As explained above, we look for evidence of net, last, and first fixation bias in the gain condition and a reversal of these biases in the loss condition. This provides insight into the role of visual attention in aversive choice without the need for selecting a particular model of attention.

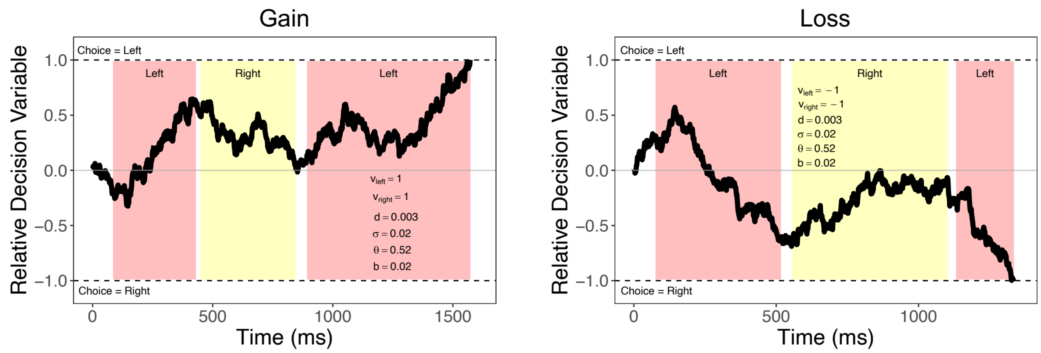

Fig. 4. aDDM Examples. (Gain) With positive value signals and an attentional parameter between $(0, 1)$, the accumulator should be biased towards the fixated option. (Loss) With negative value signals, the accumulator should be biased towards the nonfixated option. Colored vertical bands illustrate fixation locations.

In order to visualize net fixation bias, the top row of Fig. 5 depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. We corrected the probability by subtracting from each choice observation (1=left, 0=right) the proportion with which left was chosen at each $\Delta E[V]$. 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 (study 1: 95% CI = [0.25, 0.48]; study 2: 95% CI = [0.05, 0.13]), consistent with previous literature. However, we predicted a reversal of this bias in the loss condition based on predictions of the aDDM. Surprisingly, in both studies, we found no evidence of a reversal! In fact, the magnitude and direction of net fixation bias was statistically the same in both conditions (study 1: 95% CI = [-0.07, 0.11]; study 2: 95% CI = [-0.05, 0.03]).

In the middle row of Fig. 5, we plot the probability of choosing the last fixated lottery as a function of the relative expected value of the last fixated lottery. 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. We replicate last fixation bias in the gain condition (study 1: 95% CI = [0.89, 1.61]; study 2: 95% CI = [0.31, 0.85]). But once again, we do not observe any meaningful change in the loss condition as hypothesized (study 1: 95% CI = [-0.11, 0.66]; study 2: 95% CI = [-2.26, 0.97])!

In the bottom row of Fig. 5, we plot the probability of choosing the first fixated lottery as a function of the normalized relative expected value of the first fixated lottery. Note that in the absence of an attentional bias, the probability of choosing the first fixated lottery should cross 50% when the relative value of the first fixated lottery is 0. We observe this in both conditions in both studies (study 1: 95% CI = [-0.02, 0.37]; study 2: 95% CI = [-0.15, 0.09]), indicating that participants did not exhibit first fixation bias.

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. S3 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. S3 second row). In aversive choices, when relative value of the first fixated item was equal to 0, the attentional manipulation biased induced a first fixation bias in the direction of the forced fixation cross (Fig. S3 third row). In choices between gains, this is true for left fixation crosses, but not for right.

Overall, we found net fixation bias and last fixation bias persisted in aversive choices, with similar magnitudes to the gain condition. This was surprising for us, given the results of previous studies and the opposite predictions generated by the aDDM. We did not find evidence for first fixation bias, though we were able to induce a first fixation bias by manipulating the location of participants' first fixation.

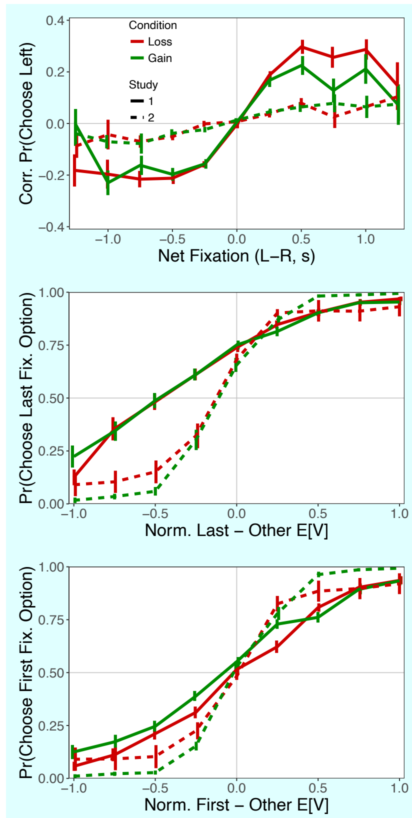

Fig. 5. Attentional Choice Biases. The top row depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. The corrected probability is computed by subtracting from each choice observation (1=left, 0=right) the proportion of which left is chosen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

aDDM and Variations

The observed attentional choice biases in the loss condition differed dramatically from what we hypothesized given the results of previous studies. In fact, if we mimic previous aDDM studies and assume (A1) value signals are negative in losses (i.e. there is no transformation of the value signal), and (A2) the attentional parameter in the aDDM is bounded between $[0, 1]$, then the aDDM *cannot* explain parallel attentional choice biases in the gain and loss conditions. It predicts there *must* be either a reversal, or at least an elimination of these biases (see Fig. S5).

In an attempt to quantify the role of attention in aversive choices, we implemented 8 variations of the aDDM that incrementally relaxed the two assumptions above and introduced viable value-signal transformations based on previous neural studies (see Table 2 in *Methods* for details). These models were fitted to each participant, separately for the gain and loss condition. The results are presented in Table 1. Each row presents the mean and standard error of parameter estimates for a particular model across all participants and the total BIC score. The total BIC score is calculated by taking the sum of BIC scores over all participants in a condition and gives a sense of the overall best-fitting model. For a more nuanced analysis of the best-fitting model by each subject, see Fig. S12 and the text below.

For the standard aDDM, we maintained that value signals were not transformed (A1) and the attentional parameter is bounded between $[0, 1]$ (A2). For the unbounded aDDM, we relaxed the bounds on the attentional parameter (A2), but maintained non-transformed value signals (A1). For 1 of the participants across both studies, the standard aDDM is the best-fitting model; for 15, the unbounded aDDM is the best-fitting model.

For the Additive aDDM (AddDDM), we implemented an additive effect of attention on the choice process instead of a multiplicative effect (Cavanagh et al., 2014; Smith & Krajbich, 2019). Value signals were not transformed (A1), and we did not impose any binding constraints on the additive effect (A2). For 29 of the participants across both studies, the AddDDM is the best-fitting model, which is the largest porportion of participants compared to any other model.

For the Divisive-Normalized aDDM (DNaDDM), we ran negative value signals through a simplified, divisive normalization algorithm that accounted for all lotteries available in each trial (A1) and relaxed the bounds on the attentional parameter (A2). Divisive normalization is not typically applied to negative values, therefore we had to make a further assumption that divisive normalization was occurring over the absolute value of the value signals, then multiplied this magnitude by -1 in the loss condition. For 1 of the participants across both studies, the DNaDDM is the best-fitting model.

For the Goal-Dependent aDDM (GDaDDM), we adjusted values according to their distance from the minimum value in a given context (A1) and relaxed the bounds on the attentional parameter (A2). For instance, in the loss condition, the minimum value is -6, so a value of -1 maps to 5 (Sepulveda et al., 2020). Note that goal-dependent remapping converts negative value signals in the loss condition to a positive space ($f : \mathbb{R}^- \to \mathbb{R}^+$). For 12 of the participants across both studies, the GDaDDM is the best-fitting model.

For the Range-Normalized aDDM (RNaDDM), we range normalized values based on condition (A1) and relaxed the bounds on the attentional parameter (A2). Similar to the GDaDDM, range normalization maps negative value signals in the loss condition to a bounded positive space ($f : \mathbb{R}^- \to [0, 1]$). For 1 of the participants across both studies, the RNaDDM is the best-fitting model.

The Range-Normalized Plus aDDM (RNPaDDM) adds an attentional constant to evidence in the RNaDDM. Mechanically, we tried this to prevent transformed value signals close to 0. Mathematically, it is equivalent to a hybrid attentional model with range normalization that assumes an additive and a multiplicative role of attention in the choice process, which are two roles that are typically juxtaposed instead of merged (Cavanagh et al., 2014; Smith & Krajbich, 2019). See Methods for more details and Supplementary for the equivalence. For 1 of the participants across both studies, the RNPaDDM is the best-fitting model.

The Dynamic Range-Normalized Plus aDDM (DRNPaDDM) is like the RNPaDDM, but where the range is adjusted trial-by-trial depending on the values that the participant has seen in that block. For example, if the range of expected values in a block is $[-\$6, -\$1]$, but the participant has only seen expected values between $[-\$4, -\$3]$ so far, then range normalization will be with respect to the latter range. For 1 of the participants across both studies, the DRNPaDDM is the best-fitting model.

Table 1. Parameter Estimates and Total BIC

Model	d		σ		b		θ		k		Total BIC	
	Gain	Loss	Gain	Loss	Gain	Loss	Gain	Loss	Gain	Loss	Gain	Loss
aDDM	0.004 (4e-4)	0.005 (5e-4)	0.053 (0.002)	0.055 (0.002)	-0.06 (0.01)	-0.08 (0.01)	0.68 (0.03)	1.00 (0.00)			71528	73930
UaDDM	0.004 (3e-4)	0.003 (3e-4)	0.053 (0.002)	0.052 (0.002)	-0.06 (0.01)	-0.08 (0.01)	0.72 (0.02)	1.56 (0.06)			71536	71743
AddDDM	0.004 (4e-4)	0.004 (4e-4)	0.053 (0.002)	0.052 (0.002)	-0.06 (0.01)	-0.08 (0.01)			1.5 (0.1)	1.7 (0.1)	71453	71639
DNaDDM	0.013 (2e-4)	0.011 (4e-4)	0.056 (0.002)	0.053 (0.002)	-0.06 (0.01)	-0.08 (0.01)	0.34 (0.08)	2.11 (0.07)			72657	72323
GDaDDM	0.005 (3e-4)	0.007 (5e-4)	0.053 (0.002)	0.052 (0.002)	-0.06 (0.01)	-0.08 (0.01)	0.72 (0.03)	0.34 (0.06)			71490	71621
RNaDDM	0.012 (2e-4)	0.012 (3e-4)	0.055 (0.002)	0.055 (0.002)	-0.06 (0.01)	-0.08 (0.01)	0.51 (0.06)	-0.03 (0.10)			72081	73254
RNPaDDM	0.009 (3e-4)	0.009 (4e-4)	0.053 (0.002)	0.052 (0.002)	-0.06 (0.01)	-0.08 (0.01)	2.25 (0.07)	1.89 (0.14)	1.5 (0.1)	1.1 (0.1)	71926	72140
DRNPaDDM	0.006 (4e-4)	0.007 (4e-4)	0.054 (0.002)	0.052 (0.002)	-0.06 (0.01)	-0.07 (0.01)	1.45 (0.09)	1.20 (0.11)	1.2 (0.1)	1.3 (0.1)	72815	73086

Mean, SE, and Total BIC of the point estimates across all subjects in both studies.
Lowest Total BIC scores by condition emphasized in red.

Overall, the AddDDM and GDaDDM had the lowest total BIC scores in the gain and loss conditions, respectively (see Table 1). Combining both conditions, the AddDDM was the best-fitting model for the most participants (29), while the GDaDDM and UaDDM were the best fitting models for nearly everyone else (12 and 15). Further model-based results will be based on the AddDDM and GDaDDM, and we will reserve the remaining results for the other variations of the aDDM for the Supplementary (see Fig. 6 - Fig.11).

Fig. 6 plots individual-level parameter estimates in the loss condition as a function of their counterpart in the gain condition for both the AddDDM and the GDaDDM. We focus first on the AddDDM. In study 1, the drift rate parameter did not differ across conditions. In study 2, it was slightly larger in the gain condition ($d_{Gain} - d_{Loss}$: $p_{\text{study 1}}$=0.308; $p_{\text{study 2}}$=0.008), but, on average, the difference (4.8e-4) was near negligible. The noise, starting point bias, and value-independent attentional parameters did not see cross-condition differences ($s_{Gain} - s_{Loss}$: $p_{\text{study 1}}$=0.279; $p_{\text{study 2}}$=0.701. $b_{Gain} - b_{Loss}$: $p_{\text{study 1}}$=0.054; $p_{\text{study 2}}$=0.703. $k_{Gain} - k_{Loss}$: $p_{\text{study 1}}$=0.917; $p_{\text{study 2}}$=0.103). Note that the attentional parameter k is positive in both the gain and loss condition, suggesting that attention pulls choices towards the fixated option, regardless of its expected value.

Next, we focus on the GDaDDM. The drift rate in the loss condition was larger than in the gain condition in study 1, but this significant difference was not replicated in study 2 ($d_{Gain} - d_{Loss}$: $p_{\text{study 1}}$=0.000; $p_{\text{study 2}}$=0.260). Noise did not vary significantly across conditions in either study ($s_{Gain} - s_{Loss}$: $p_{\text{study 1}}$=0.315; $p_{\text{study 2}}$=0.427). Starting point bias was slightly larger in the gain condition in study 1, but this did not replicate in study 2 ($b_{Gain} - b_{Loss}$: $p_{\text{study 1}}$=0.044; $p_{\text{study 2}}$=0.280).

On average, the difference in starting point bias was 0.04, which is small but represents a meaningful change when compared to the average magnitude of the bias. The attentional parameter was significantly larger in the gain condition in both studies ($\theta_{Gain} - \theta_{Loss}$: $p_{\text{study 1}}$=0.000; $p_{\text{study 2}}$=0.027). In study 1, θ_{Gain} was 0.45 larger than θ_{Loss}, and in study 2, it was 0.27 larger. Both of these results imply significantly more attentional discounting is occurring in the loss condition. Note that for a handful of participants, the attentional discounting parameter falls outside of its traditional bounds at $[0, 1]$, but for the most part, estimates are still within the bounds. This suggests that attention is still pulling choices towards the fixated option, even if the fixated option has a negative expected value, since these negative values are remapped to positive values and the nonfixated value is multiplied by the attentional parameter. When $\theta < 0$, this is still true, albeit with an extreme level of attentional bias. It is when $\theta > 1$ that the impact of attention on choice flips, and choices are pushed away from the fixated option. Oddly enough, we observe more cases of $\theta > 1$ in the gain condition than in the loss condition, though the number of cases is relatively few and most estimates stick roughly close to 1. Without confidence intervals, we cannot say if they differ significantly from the traditional upper bound 1.

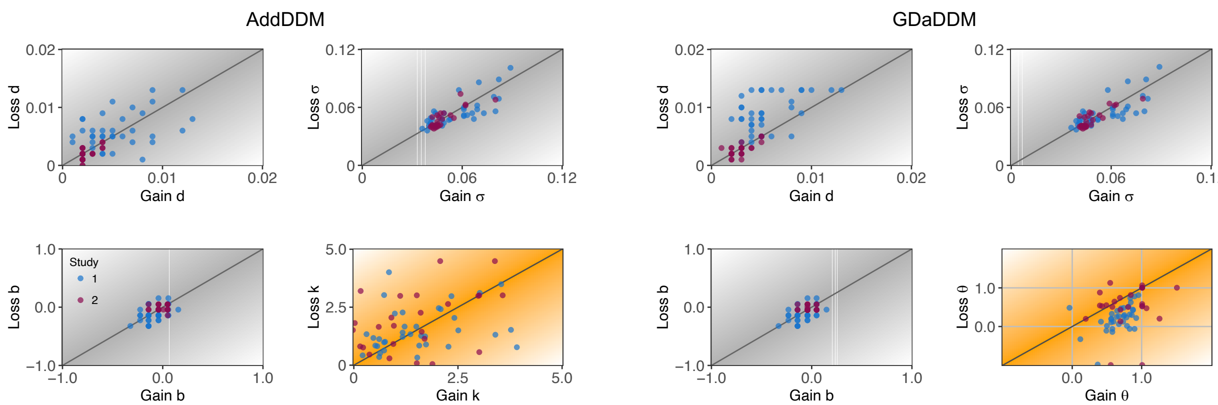

Fig. 6. Comparison of Individual Estimates. Drift rate, noise, bias, and attentional parameter estimates in the loss condition as a function of their counterpart in the gain condition. AddDDM is the Drift-Diffusion-Model with a value-independent attentional parameter. GDaDDM is the Goal-Dependent Drift-Diffusion-Model that subtracts the minimum possible expected value in a block from each lottery's expected value, converting negative values to positive distances from the minimum.

Fig. 7 plots out-of-sample choice, RT, and attentional bias predictions based on estimates from the AddDDM and GDaDDM. Both models qualitatively replicate choice accuracy in both studies, though both are better in Study 2 than in Study 1. Both models do a poor job of replicating RTs when choices are difficult, but become more accurate as choices grow easier. This may be indicative of a collapsing boundaries model. Note that both models are capable of qualitatively predicting parallel attentional biases in the gain and loss conditions, which is impossible without adding or relaxing assumptions to the standard aDDM (as seen in Fig. S5 and S6).

Discussion

To investigate the role of attention in the aversive choice process, we ran two binary choice experiments with choices in gains and in losses. In both experiments, we found that the average quality

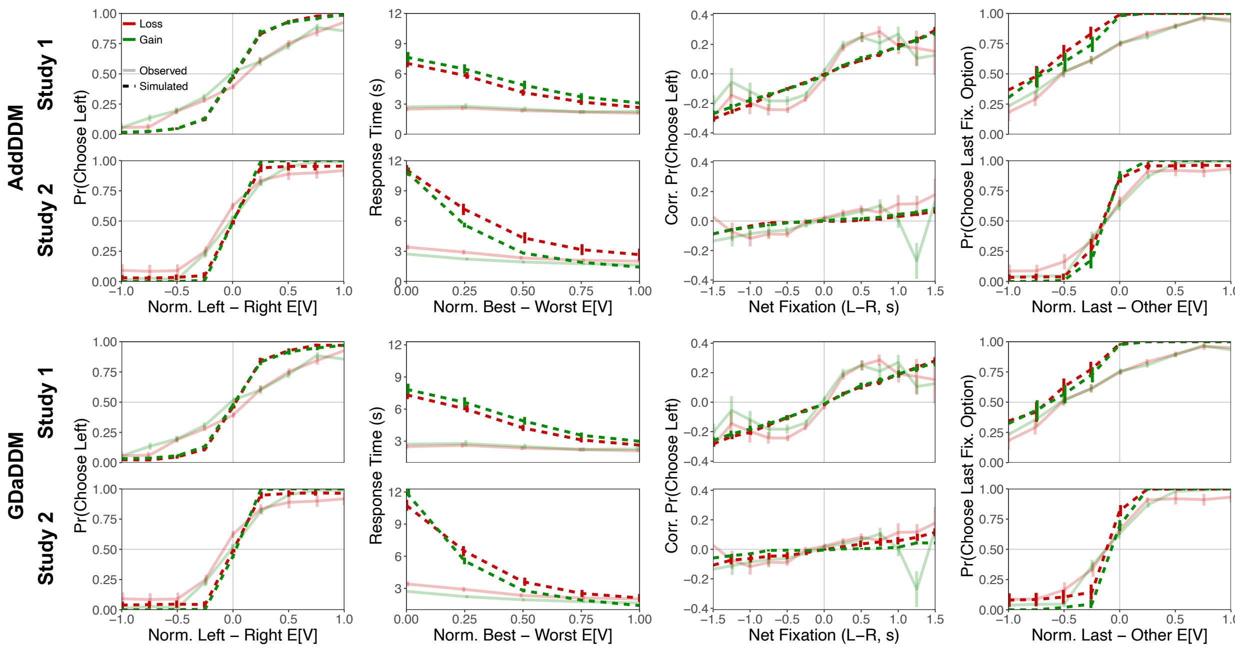

Fig. 7. Out-of-Sample Predictions for the AddDDM and GDaDDM. The first plot in each row depicts the probability of choosing the left lottery as a function of its normalized relative expected value. The second plot in each row depicts response times as a function of the normalized difference between the best and worst expected value. The third plot in each row depicts the corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. Probabilities were corrected as described above. The fourth plot in each row depicts the probability of choosing the last fixated option as a function of the normalized expected value difference between the last fixated option and the other option. Predictions are based on 10 simulated datasets using estimates fitted to the odd-trial data and fixation properties from the even-trial data. These are compared against data from the even-trial data. The top two rows correspond to predictions from the AddDDM; the bottom two rows correspond to predictions from the GDaDDM. Each row corresponds to predictions for a specific study. Error bars denote SEs across the means of all subjects (simulated datasets were pooled).

of choices and the fixation process did not differ by much across conditions. However, attentional choice biases, like net fixation bias and last fixation bias, were parallel between the two conditions, which was surprising given the predictions of the standard aDDM and previous work. In other words, our results suggest that regardless of whether the choice is appetitive or aversive, attention is pulling choices in the direction of the attended item. In order to explain the lack of attentional bias reversals in the loss condition, we fit 8 variations of the aDDM that incrementally varied value signal transformations and the role of attention. We found that the AddDDM, which incorporates a value-independent attentional bias, was the best-fitting model in the gain condition and that the GDaDDM, which transforms value signals into positive distances from the minimum possible value in a context, was the best-fitting model in the loss condition. We also found that despite the lack of first fixation bias observed in the data, we were still able to introduce first fixation bias by manipulating the location of the inter-trial fixation cross.

These results have important implications for any environment where aversive choices are encountered. In a representative survey of over 1,300 Americans, an estimated 30% reported difficulty in choices between basic necessities (like food, housing, and heat) and health care (NORC at the

University of Chicago & West Health Institute, 2018). Understanding how attention plays a role in these important, but aversive, decisions might suggest interventions that choice architects can employ to help individuals make better decisions (Johnson et al., 2012). In politics, voters are occasionally faced with choosing the candidate they dislike the least. For instance, in a poll by NBC News in 2016, roughly 60% of Americans reported that they either "disliked" or "hated" both Hilary Clinton and Donald Trump, the two presidential candidates for the Democratic and Republican parties that year. Funnily, the top cited reason for voting for one candidate was "disliking the other candidate" in both cases (Hartig, Lapinski, & Psyllos, 2016). Our results echo the notion that when both candidates are so widely disliked, "any publicity is good publicity".

Given our model-fitting results, there are two interpretations of what attention is doing during the aversive choice process. First, as suggested by Cavanagh et al. (2014), attention may be providing a fixed, positive, additive boost to the evidence accumulated in favor of the fixated option, regardless of whether that option is appetitive or aversive. Contrary to Smith and Krajbich (2019), this would suggest that the effect of attention on choice is independent of value.

The second interpretation is that attentional discounting is occurring in both appetitive and aversive choices, but that raw value signals are not used during the comparison process. Instead, value signals are transformed into distances from the worst possible outcome and then compared. This is consistent with the hypothesis that attention aids in the accumulation of *goal-relevant* evidence that is transformed according to the goal at-hand (Sepulveda et al., 2020). There is also neural evidence that avoiding aversive outcomes are encoded as rewards in the orbitofrontal cortex, a region of the human brain that has been previously implicated in encoding stimulus reward values (Kim, Shimojo, & O'Doherty, 2006). Fitting the GDaDDM also results in attentional parameter estimates in both gain and loss conditions that are consistent with Bayesian accounts of attention in optimal information sampling (Jang et al., 2021; Callaway et al., 2021). How do I say this more professionally... For these reasons and a few shortcomings listed below, this is the interpretation that the authors view as most plausible.

There are two potential reasons why the AddDDM fit our data well, but these reasons also suggest that it might not generalize. First, in study 1, the range of expected values of the lotteries was not very large, which would serve to mask any relationship between attention and value in the choice process. In Fig. S13, we plotted corrected RTs as a function of the overall value of the choice and found that corrected RTs did not significantly fluctuate within the small range of overall values in study 1. It's possible that there is no relationship (which would favor the AddDDM), but the range of overall values in study 1 may not be sufficient for this conclusion. It's also possible that this limited range negatively impacted the fit of the range-normalized aDDM, which would be more suited to behavior over larger ranges.

Second, in study 2, we find an unusual parabolic relationship between corrected RTs and overall value, which by construction cannot be explained by value differences (see Fig. S13). Not sure we want to put this here... We believe this relationship is due to the range of probabilities that participants encounter at different overall values. For instance, when absolute overall values are > 10, probabilities range from $(0.4, 0.9)$. When absolute overall values are < 5, probabilities range from $(0.09, 0.45)$. And when absolute overall values are closer to the middle, like 6 or 7, probabilities range from $(0.09, 0.91)$. The range of outcomes does not vary much in the different groups. Because of the nonlinear relationship between corrected RTs and overall value, it's possible that the best-fitting model would be one that simply assumes no relationship, like the AddDDM. However, there is clearly a relationship here that needs further exploration, though it is beyond the scope of this paper.

There are other modifications of the aDDM that we did not consider in this paper. One of the most apparent modifications to consider would be to introduce collapsing boundaries or an urgency signal to the aDDM. Recall that in Fig. 7, RTs in difficult choices were greatly over-estimated, regardless of study, condition, or model. This is indicative that the aDDM is struggling to make difficult decisions, but does not account for any "impatience" that humans may exhibit when faced with the same choices. Second, we chose not to model non-decision time (NDT) and instead used observed latencies to first fixation as a rough proxy. This is because we manipulated the location of the fixation cross in study 2 to sometimes overlap with one of the lottery locations. This would mean that NDT would vary trial-by-trial according to the location of the fixation cross. Fitting a distribution of NDTs is currently not available with the aDDM toolbox that we are using, so we chose not include this parameter and instead used an observed proxy. Note that in study 2, the latency to first fixation (and therefore NDT) is 0 when the fixation cross overlaps with one of the lottery locations. This is unrealistic and interferes with the quality of our model fits.

There are other limitations to the generalizability of our findings. First, while our study is limited to binary choice, many decisions require one or more selections from more than 2 options. The role of attention in the choice process may vary depending on the complexity of the environment in which a decision is made. Second, we chose to focus on risky choices, but aversive choice extends to any form of stimulus (e.g. food, social decisions, experiences, voting). Further work is needed to ensure that these results extend to other choice domains.

In summary, our results describe the role of attention in the aversive choice process. Contrary to our hypothesis, attention to an aversive option still pulls choices towards that option, despite its negative value. This is consistent with the hypothesis that attention modulates the accumulation of goal-relevant evidence during the choice process. Future research must extend this work to other choice domains and reconcile these results with previous findings of attentional choice bias reversals in aversive food choice.

Methods

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 subjects 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 (see *Procedures*).

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. 91 participants were recruited to study 1, of which 19 were excluded for failing our participant filter, leaving 72 participants (age: mean = 25 years, range = 18-41; 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.

69 participants were recruited to study 2, but 6 were excluded due to a change in the instructions and 13 were excluded for failing the participant filter, leaving 50 participants in the numeric study (age: mean = 27.68 years, range = 18-55; 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). Participants were equaly split between the exploratory and confirmatory sample as above.

The number of participants and trials per participant were chosen based on related studies that have shown that this sample size provides reliable estimates of the parameters and effects of interest. All participants gave informed consent, and all experiments were approved by Caltech's Institutional Review Board.

Procedures

Study 1. Participants made decisions in two conditions: (1) a *gain* condition in which both options are lotteries with probabilities over \$0 or \$10, and (2) a *loss* condition with similar options, but the outcomes are \$0 or -\$10. Lotteries were represented using 100 colored dots, with white representing the probability of no payment, green representing the probability of gaining \$10, and red representing the probability of losing \$10.

Stimuli in each trial were randomly generated. A grey circle would appear on the left and right sides of the screen. In each circle were 100 randomly placed dots with no overlap. An integer p was uniformly drawn from 45 to 55, and this would indicate the number of green dots (gain) or red dots (loss). $100 - p$ determined the number of white dots.

Trials started with a 1 s fixation cross. Subjects indicated their choices using the arrow keys and were free to respond at their own pace. Upon selecting an option, feedback was provided about which option was selected for 1 s. Subjects completed 400 trials, split into 2 blocks of 200 trials each. 1 block was in the gain condition, the other in the loss condition, order counterbalanced.

After the experiment was over, subjects 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 (deducted) to this amount.

Study 2. Similar to study 1, participants made decisions between lotteries in a gain and a loss condition. However, instead of presenting lotteries as dots, we presented them in numeric format. Each lottery was presented as one outcome with one probability p. We took extra precaution during the instructions to ensure that participants understood each lottery had an implicit \$0 outcome with probability $1-p$. The outcomes were bounded between [$\pm$\$6, $\pm$\$12], depending on the condition, and differences in expected value ranged from \$0 to $\pm$\$4. Lottery outcomes and probabilities were designed in a way to prevent obviously dominant choices. For instance, if lottery A had a better outcome than lottery B, then it's probability was strictly bounded above by the probability in lottery B.

Trials started with a 1 s fixation cross. Participants indicated their choices using the arrow keys and were free to respond at their own pace. Upon selecting an option, feedback was provided about which option was selected for 1 s. Participants completed 340 trials, split into 4 blocks of 85 trials each. 2 blocks were in the gain condition, the others in the loss condition, order counterbalanced.

4 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 (a) \$10 with $p = 1$ or (b) \$0 with $p = 1$. In the loss condition, (a) \$0 with $p = 1$ or (b) -\$10 with $p = 1$. If participants chose (b) on one of these trials, we counted it as one failed sanity check.

Each sanity check trial started with the fixation cross in the center of the screen, between the two options. The 81 remaining trials were equally split (27 trials) 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.

After the experiment was over, subjects drew two numbers between 1 and 170 out of an urn, the first for a lottery in block 1 and the second for a lottery in block 2. The lotteries were played out, participants were paid a \$40 show-up fee, and gains (losses) earned from the experiment were added (deducted) to this amount.

Eye-Tracking

Eye-tracking data was collected using an Eyelink 1000 sampling at 500 Hz. Subjects were instructed to sit approximately 60 cm from a 1920 $\times$ 1080 pixel monitor. Lottery stimuli in study 1 were 300 $\times$ 300 pixels. 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 of the same type (e.g. right-right-right-right) since these types of fixation sequences are typically due to eye-tracker noise or blinking and tend to be short. 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

We collect two separate datasets as a means to explore the data and confirm our results in a separate sample. We use one dataset for exploration, pin down our analyses, then attempt to replicate the results from the exploratory dataset in a second, confirmatory dataset. In the spirit of meta-analysis, if the results from the exploratory and confirmatory datasets are similar, we also provide results on the pooled sample and describe summary statistics in terms of the pooled estimates.

Computational Model

We use a variation of the Drift-Diffusion-Model (Gold & Shadlen, 2007; Ratcliff & McKoon, 2008) called the Attentional Drift-Diffusion-Model (aDDM) (Krajbich et al., 2010), where value sampling is affected by the location of one's gaze. Decision-makers integrate noisy value signals into a relative-decision-value accumulator that evolves over time, RDV_t. The accumulator starts at an initial location $RDV_0 = b$, incorporating some bias towards one of the two options if $b \neq 0$. Once RDV_t crosses one of two pre-specified boundaries (± 1), a choice is made based on the identity of the boundary (e.g. hitting upper boundary indicates a choice for left option, hitting lower indicates right). The evolution of this accumulator looks like the following diffusion process:

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

where ϵ_t is i.i.d. white Gaussian noise with variance σ^2. At every point in time, the evidence in the diffusion process depends on the location of the decision-maker's gaze and is given by:

$$\mu_t := \begin{cases} d[f(V_L) - \theta f(V_R)] & \text{if looking left at time } t \\ d[\theta f(V_L) - f(V_R)] & \text{if looking right at time } t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where d is the drift rate parameter controlling the speed of integration, $f(V_i)$ is a function the value of option i, and θ is an attentional discounting parameter that discounts the value of the nonfixated option. Importantly, the aDDM takes fixations as exogenous to the model and is therefore agnostic to modeling the fixation process, though variations of the aDDM with endogenous fixations do exist (Gluth, Kern, Kortmann, & Vitali, 2020).

In this paper, we implement 7 different variations of the aDDM using concepts from cognitive neuroscience. Each variation differs over 2 assumptions about the model (see Table 2). Assumption

1 (A1) deals with the bounds of the attentional parameter in the aDDM. Assumption 2 (A2) deals with the functional form of $f(\cdot)$.

As in Krajbich et al. (2010) and Smith and Krajbich (2018), the standard aDDM assumes the attentional parameter, θ, is bounded between $[0, 1]$ (A1), and expected value signals are used as inputs to the model (A2). This model has the benefits of being straightforward and intuitive.

The unbounded aDDM (UaDDM) relaxes the bounds on the attentional parameter (A1) while still using expected value signals as inputs (A2). In Eum et al. (2023), fitting the UaDDM to appetitive food choices still resulted in attentional parameter estimates that did not significantly differ from $[0, 1]$.

The additive model of attention (AddDDM) refers to a class of attentional models that assumes the effect of attention on choice is independent of the stimulus values (Cavanagh et al., 2014; Smith & Krajbich, 2019). In the AddDDM, this translates to no multiplicative attentional bias ($\theta = 1$) and an additive attentional parameter, k, that is added or subtracted from the value difference depending on where the decision-maker is looking.

The aDDM, UaDDM, and AddDDM represent a class of models that purely focuses on modeling the impact of attention on the choice process. However, it may be important to consider modifications to the aDDM that are not related to the role of attention. For instance, the Divisive Normalized aDDM (DNaDDM) considers the case where value signals that serve as inputs to the model are modulated by other factors within a trial (Louie, Khaw, & Glimcher, 2013; Webb, Glimcher, & Louie, 2020, 2021; Keung, Hagen, & Wilson, 2020). Here we transform value signals with a simplified divisive normalization function (Bavard & Palminteri, 2023) that normalizes the value of an option with respect to the absolute, overall value of the decision. Note that to the best of the authors' knowledge, divisive normalization has not been applied to choices between negatively-valued options. Since there was no precedent on how to implement divisive normalization in aversive choice, we opted to maintain the sign of the values by only taking the absolute value of the denominator.

Goal-dependent evidence in the aDDM (GDaDDM) provides another way to implement context-dependent value signals, this time across-trials instead of within-trial like divisive normalization. There is neural evidence that suggests avoiding an aversive outcome is encoded as a reward (Kim et al., 2006). Therefore in the GDaDDM, we re-code value signals as distances from the minimum possible value in a block (Sepulveda et al., 2020). Note that this converts all negative values to weakly positive distances.

Similar to the goal-dependent transformation, we also consider range normalization in the aDDM (RNaDDM). There is neural evidence that suggest value signals are range normalized in the orbitofrontal cortex (Rangel & Clithero, 2012; Padoa-Schioppa, 2009). We range normalize values by taking their proportional position in the range of all possible expected values within a block, regardless if those expected values have been observed yet. This looks like a scalar transformation of goal-dependent value signals in the GDaDDM (Sepulveda et al., 2020). Note that range normalizing negative value signals also maps negative values to the positive space, though this time bounded by $[0, 1]$.

The Range Normalized Plus aDDM (RNPaDDM) takes the RNaDDM a step further by implementing both an additive and multiplicative effect of attention on choice. See the Supplementary for the equivalence of the RNPaDDM to a model that implements both multiplicative and additive attentional effects on the choice process.

The Dynamic Range Normalized Pluss aDDM (DRNPaDDM) behaves like the RNPaDDM, except the range is now adjusted trial-by-trial based on past and current observed expected values within a block.

Table 2. Models and Assumptions.

Model	A1: θ	A2: Value Function	
aDDM	$\theta \in [0,1]$	$f(V_i) = E[V_i]$	
UaDDM	Unbounded	$f(V_i) = E[V_i]$	
AddDDM	$\theta = 1$	$f(V_i) = E[V_i] \pm \hat{k}$	$\hat{k} = \frac{k}{2}$
DNaDDM	Unbounded	$f(V_i) = \frac{E[V_i]}{\lvert E[V_L] + E[V_R] \rvert}$	
GDaDDM	Unbounded	$f(V_i) = E[V_i] - \min_{\text{block}}(E[V])$	
RNaDDM	Unbounded	$f(V_i) = \frac{E[V_i] - \min_{\text{block}}(E[V])}{\max_{\text{block}}(E[V]) - \min_{\text{block}}(E[V])}$	
RNPaDDM	Unbounded	$f(V_i) = \frac{E[V_i] - \min_{\text{block}}(E[V])}{\max_{\text{block}}(E[V]) - \min_{\text{block}}(E[V])} + \hat{k}$	$\hat{k} = \frac{k}{1-\theta}$
DRNPaDDM	Unbounded	$f(V_i) = \frac{E[V_i] - \min_{\text{history}}(E[V])}{\max_{\text{history}}(E[V]) - \min_{\text{history}}(E[V])} + \hat{k}$	$\hat{k} = \frac{k}{1-\theta}$

$\min_{\text{block}}$ and $\max_{\text{block}}$ are operators over all possible values in a block.
$\min_{\text{history}}$ and $\max_{\text{history}}$ are operators over all values previously and currently seen in a block.
AddDDM: $+\hat{k}$ if i fixated. $-\hat{k}$ if i nonfixated.
$\hat{k}$ written to make k comparable across models.

aDDM Fitting

We fit odd-numbered trials to the aDDM using a algorithm developed by Tavares et al. (2017), with an updated toolbox currently under development in the Rangel Neuroeconomics Lab (`https://github.com/aDDM-Toolbox`). Because evidence in the model varies moment-to-moment, the likelihood function does not have a closed-form solution, and instead needs to be numerically approximated. The algorithm used in this paper discretizes both the time space (10 ms time-steps) and the accumulator space, allowing it to efficiently calculate the probability of crossing a decision boundary at every time-step. The space of possible parameters estimates is split into a grid. A set of estimates is pulled from this space and a likelihood is numerically approximated for that set using the algorithm described above. The grid initiates with a relatively coarse resolution, and selects a set of estimates. Then a finer grid is defined around the selected estimates and the process is repeated. This cycle repeats until the change in negative log-likelihood is less than 0.01%. The algorithm yields precise point-estimates for parameters of the aDDM in a fraction of the time previously required, without relying on approximations of the moment-to-moment evidence (Thomas, Molter, Krajbich, Heekeren, & Mohr, 2019; Lombardi & Hare, 2021; Smith, Krajbich, & Webb, 2019).

This is kinda shit. Maybe rewrite this more like how it's written in Tavares Page 4.

Out-of-Sample Simulations

Even-numbered trials were set aside as out-of-sample data to compare with simulated behavior from the aDDM fit to odd-numbered trials. We simulated 10 datasets for every participant and condition, using the same lotteries encountered during the experiment. Each trial was simulated as follows. Fixation durations statistics were sampled from their empirical distributions in the even trials, conditional on the gain or loss condition. For example, in a loss-condition trial, RDV was initialized at the bias estimate, then evolved only according to the noise up to the duration of the sampled latency to first fixation. Afterwards, a maximum first fixation duration and location was sampled from the loss condition, and RDV evolved according to the drift, noise, and attentional discounting estimates. If a decision boundary was crossed before the maximum duration was reached, then the process was terminated and the choice and RT were recorded. Otherwise, a saccade and middle fixation duration were sampled from their empirical distributions, and the process would repeat until a decision boundary was crossed. We assume the value of the nonfixated option is known during the first fixation, which is unrealistic and reduces the quality of our model fits.

Hierarchical regressions

All regressions reported in the paper are based on standard hierarchical models with random coefficients and use weakly informative priors. Regressions were implemented using the brms package ((Bürkner, 2017)) in R (version 4.3.1.; R Core Team (2023)). Posterior distributions were estimated using 3 chains for a total of 9,000 burn-in samples and 9,000 samples from the posteriors.

Author Contributions A.R. and B.E. designed research; S.G. and B.E. collected data; B.E. analyzed data; and B.E. and A.R. wrote the paper.

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Competing Interests The authors declare no competing interests.

Open Practices All data and code are available for download at the Rangel Neuroeconomics Lab website (`www.rnl.caltech.edu`). The design and analysis plans for this study were not preregistered.

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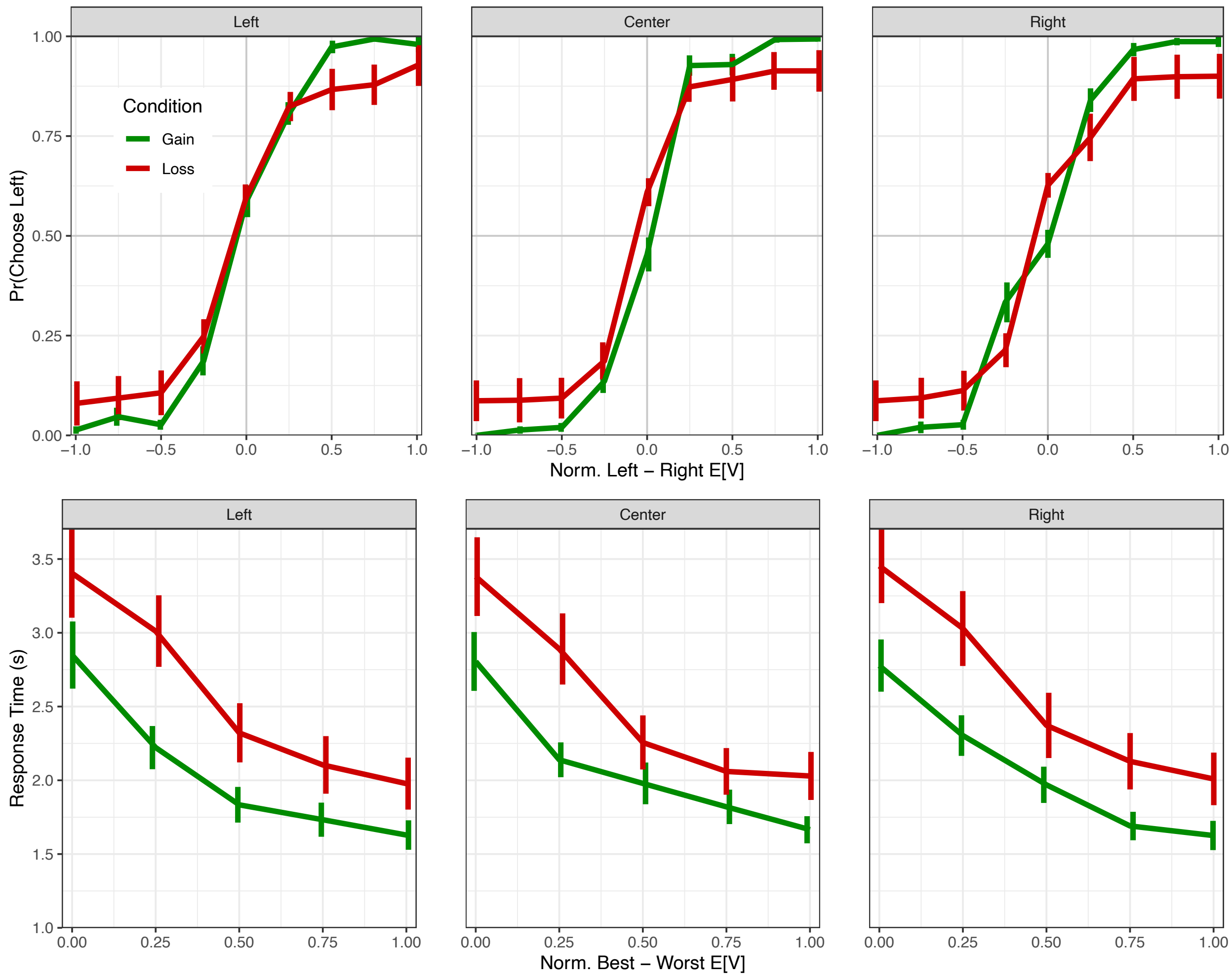
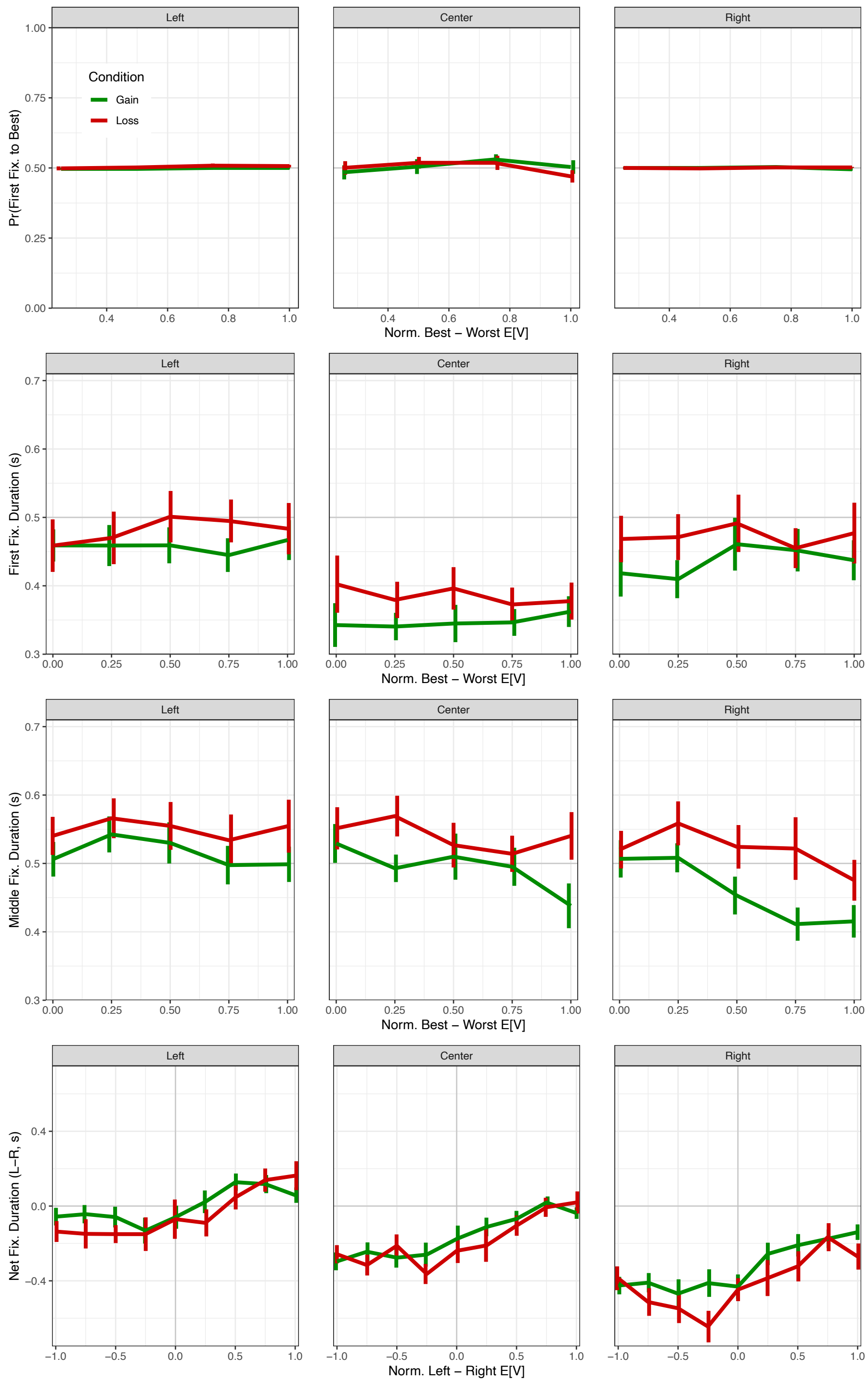
Supplementary Material

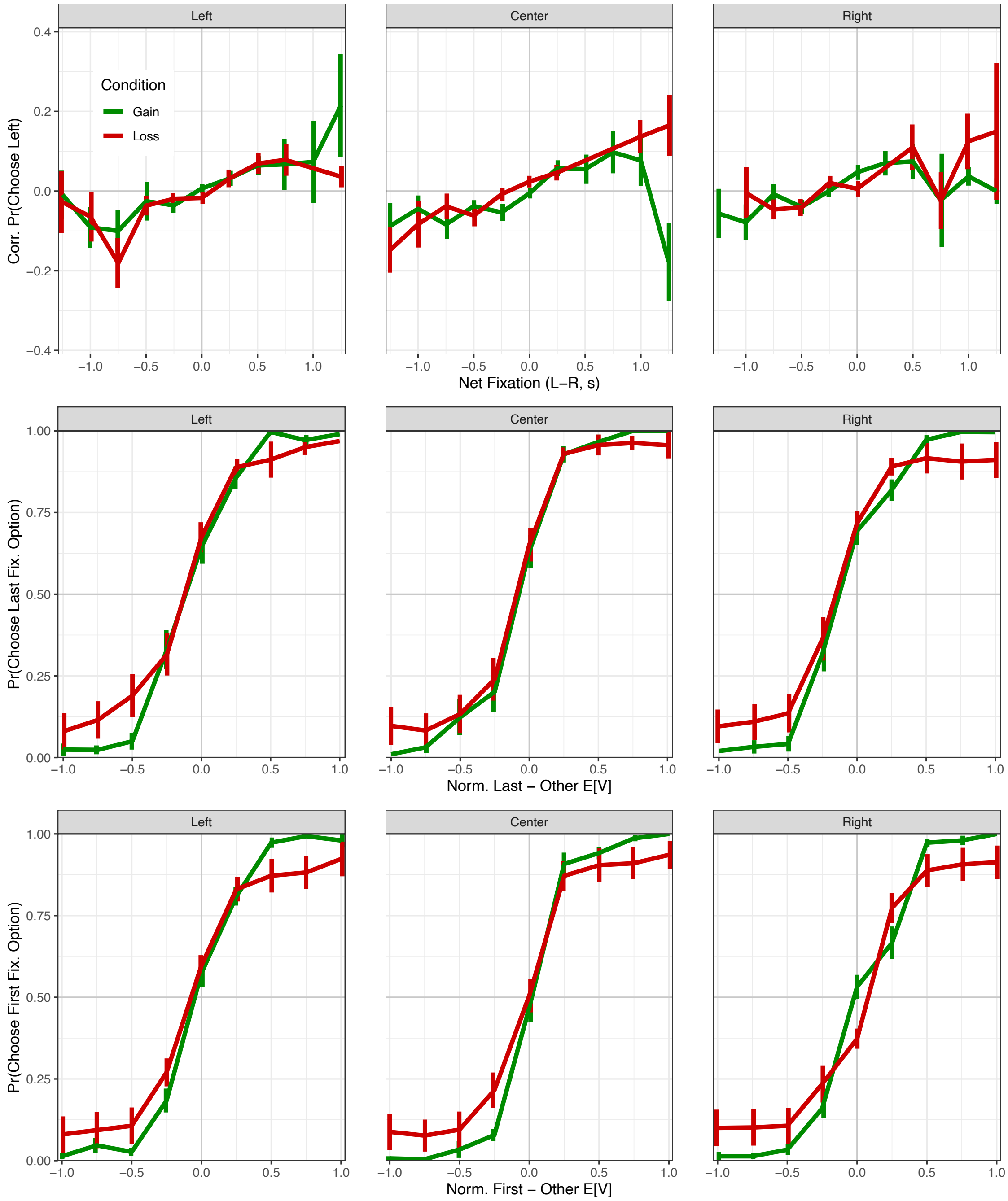
Attentional Manipulations



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

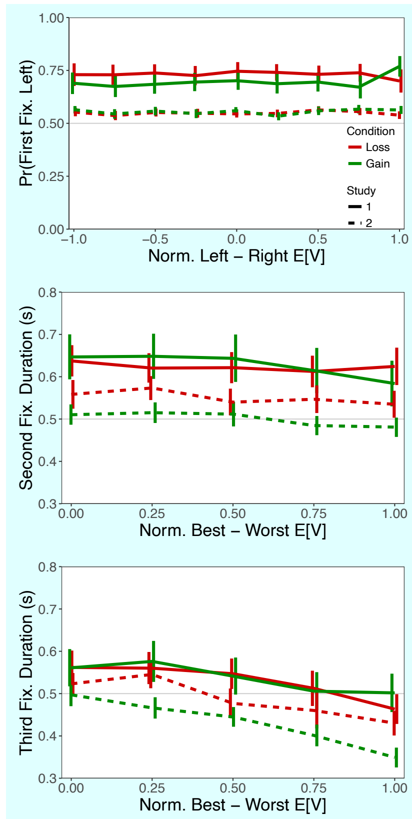


Supplementary Fig. 2. Fixation Process with Attentional Manipulations. The first row depicts the probability of first fixating on the best lottery as a function of normalized choice difficulty. The second row depicts the first fixation durations as a function of normalized choice difficulty. The third row depicts average middle fixation durations as a function of normalized choice difficulty. The fourth row depicts the net fixation duration to the left lottery as a function of the normalized expected value difference. Columns denote the location of the fixation cross. Error bars denote standard error of the mean across participants.



Supplementary Fig. 3. Attentional Choice Biases with Attentional Manipulations. The top row depicts the corrected probability of choosing the left lottery as a function of the net fixation time to the left lottery. Corrected probabilities are calculated by taking the choice observation (1=left, 0=right) and subtracting the proportion of times left was chosen at each value difference. The middle row depicts the probability of choosing the last fixated option as a function of the normalized relative expected value of the last fixated lottery. The bottom row depicts the probability of choosing the first fixated option as a function of the normalized relative expected value of the first fixated lottery. Columns denote the location of the fixation cross. Error bars denote standard error of the mean across participants.

Additional Fixation Properties



Supplementary Fig. 4. Additional Fixation Properties. The top row depicts the probability of first fixating left as a function of choice difficulty. The middle row depicts the second fixation duration as a function of the normalized relative value. The bottom row depicts the third fixation duration as a function of the normalized relative value.

Multiplicative and Additive aDDM

The RNPaDDM and DRNPaDDM represent a combination of both the multiplicative and additive aDDM. Evidence in either model can be written as:

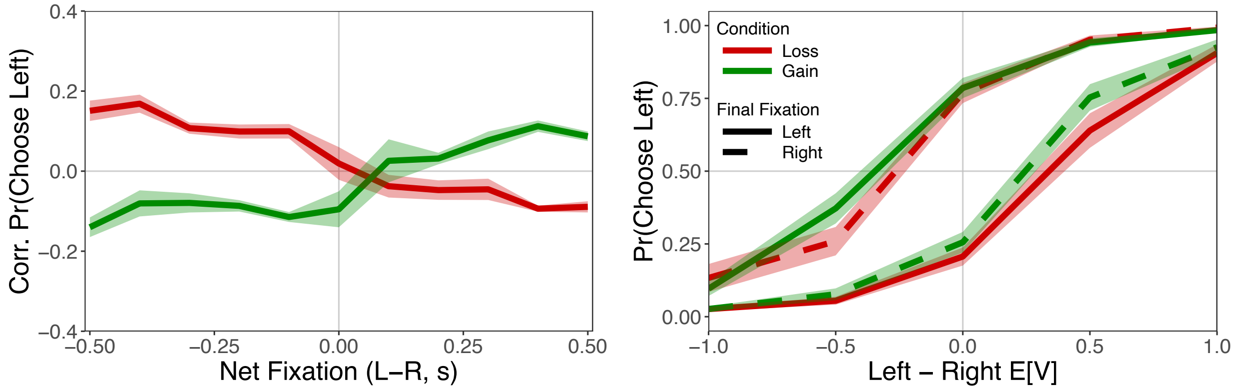
$$\mu_t := \begin{cases} \left(V_L^N + \dfrac{k}{1-\theta}\right) - \theta\left(V_R^N + \dfrac{k}{1-\theta}\right) & \text{if looking left at time } t \\ \theta\left(V_L^N + \dfrac{k}{1-\theta}\right) - \left(V_R^N + \dfrac{k}{1-\theta}\right) & \text{if looking right at time } t \\ 0 & \text{otherwise} \end{cases}$$

where V_i^N is the range normalized value of item i, regardless of whether the range is dependent on possible values in a block or on history within a block. After some rearranging, this equates to:

$$\mu_t := \begin{cases} V_L^N - \theta V_R^N + k & \text{if looking left at time } t \\ \theta V_L^N - V_R^N - k & \text{if looking right at time } t \\ 0 & \text{otherwise} \end{cases}$$

which nests the AddDDM with range normalization if $\theta = 1$. If $\theta \neq 1$, then this represents a combination of a multiplicative and an additive effect of attention on the choice process.

aDDM-Variation Attentional Choice Bias Predictions



Supplementary Fig. 5. aDDM Simulations Using $\theta \in (0, 1)$ and Negative Value Signals. Other aDDM parameters and fixation properties were sampled from distributions similar to those found in the visible condition in Eum et al. (2023). (Left) Corrected probability of choosing the left lottery as a function of the net fixation to the left lottery. (Right) The probability of choosing the left lottery as a function of the relative value of the left lottery and the location of the last fixation. Ribbons indicate standard error of the mean across subjects.

figures/standard_aDDM_predictions.pdf

Supplementary Fig. 6. Standard aDDM Predictions.

figures/unbounded_aDDM_predictions.pdf

Supplementary Fig. 7. Unbounded aDDM Predictions.

figures/DNaDDM_predictions.pdf

Supplementary Fig. 8. DNaDDM Predictions.

figures/RNaDDM_predictions.pdf

Supplementary Fig. 9. RNaDDM Predictions.

figures/RNPaDDM_predictions.pdf

Supplementary Fig. 10. RNPaDDM Predictions.

figures/DRNPaDDM_predictions.pdf

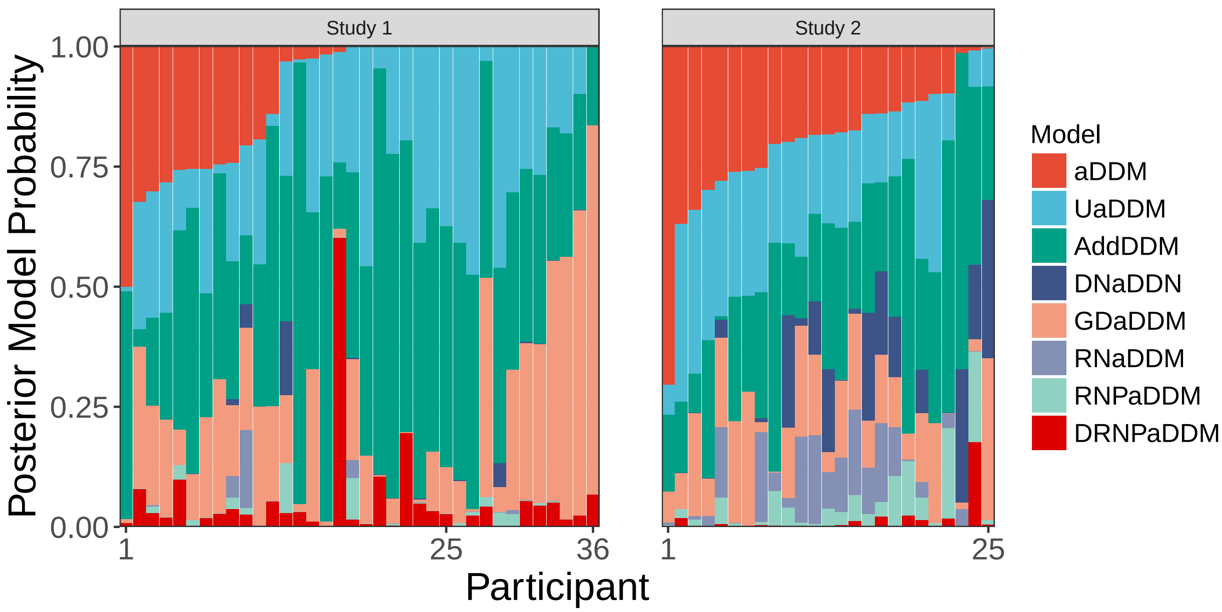
Supplementary Fig. 11. DRNPaDDM Predictions.

Posterior Model Probabilities

Posterior model probabilities are calculated as in Hawkins, Forstmann, Wagenmakers, Ratcliff, and Brown (2015), given by Wasserman (2000). Assuming a uniform prior across all models and that the data generating model is contained in the set of models that we consider, we employ a BIC-approximated posterior model probability:

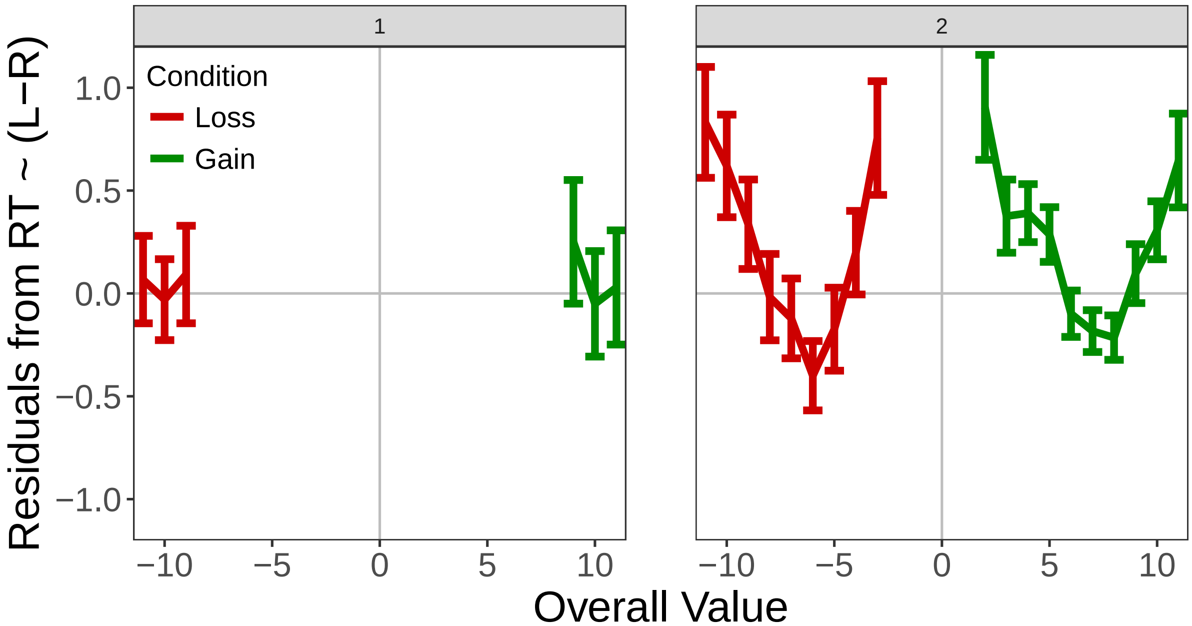
$$\Pr(m_i|Data) = \frac{e^{-.5\mathrm{BIC}(m_i|Data)}}{\sum_{j=1}^{M} e^{-.5\mathrm{BIC}(m_j|Data)}}$$

where m_i is model i out of a total of M models.



Supplementary Fig. 12. Posterior Model Probabilities. BIC-approximated posterior model probabilities for all models for each participant in studies 1 and 2.

RT and Overall Value



Supplementary Fig. 13. RT and Overall Value. Residual RT as a function of the overall value of a decision in study 1 (left) and study 2 (right). Residual RT is the residuals from a linear regression of response time on the relative value of the left option. Overall value is the sum of the values of all options.

Supplementary Tables

Supplementary Table 1. Regressions associated with the basic psychometric results in Fig. 2.

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

"N." = Normalized.

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

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

Supplementary Table 2. Regressions associated with the fixation process results in Fig. 3.

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

"N." = Normalized.

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

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

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

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

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

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

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

"Corr." = Corrected. "L" = Left. "N." = Normalized.

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

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