# What is the story I want to tell in the shortest possible paragraph?

Using predictions from the aDDM, we expected that in aversive choice, attention would drive choices away from the attended option. Instead, we found attentional choice biases in the same direction as they are in choices between gains. We can reconcile with a few different attentional choice process models, but we find a behavioral signature unique to just one of those models: the reference-dependent aDDM (RaDDM). This suggests that individuals accumulate positive, reference-dependent value signals about their options, leading them to exhibit the same robust attentional choice biases seen in previous literature, even in aversive choices.

## Try to take a narrative approach and present the information in the way that I would have run the research project. It’s worth it to highlight mis-directions if they give some insight into the thought process.

# Intro. Just focus on the research question, what you hypothesized, and why?

We want to understand how attention affects aversive choice. We hypothesized that it would push choices away from the attended option based on predictions of the aDDM with negative value signals and an attentional parameter bounded above by 1. We simulated using theta between (0,1). See Bhatnagar and Orquin (2022) for meta-analysis of attentional bias estimates.

# Results. What experiment did you run to test this hypothesis? What are some model-free ways to look at changes in behavior? What are your main behavioral results? How did you select a model? Does the model-based analyses explain your main behavioral results?

Paradigm

To address this research question, we ran two studies, both involving binary, risky choices. Study 1 used perceptual stimuli. Study 2 used numeric stimuli. Both studies had two conditions: (gain) choices between positive outcome lotteries, (loss) aversive choices between negative outcome lotteries. In Study 2, we manipulated the location of the inter-trial fixation cross to try and induce a first fixation bias and causally manipulate choices.

Basic Psychometrics and Fixation Process

We checked participants’ Basic Psychometrics and Fixation Processes. In both studies, participants exhibited minor-to-negligible levels of differences between their choices, response times, and fixation processes. One notable difference was longer response times in the loss condition in Study 2. This is consistent with self-reports from some participants that they found it slightly more difficult to comprehend negative-outcome lotteries than positive-outcome lotteries. Other than this one difference, Basic Psychometrics and Fixation Process suggest that results pertaining to attentional choice biases cannot be associated with differences in the fixation process or response caution.

Attentional Choice Biases

Contrary to our predictions, participants exhibited statistically identical attentional choice biases in the gain and loss conditions. This means participants still exhibited net fixation bias and last fixation bias, despite choosing between negatively-valued options in the loss condition. We found no evidence for first fixation bias in either study, though we were able to use fixation cross manipulations to causally induce a first fixation bias. These results are not reconcilable with the current version of the aDDM.

Model Selection

There are a few attentional choice process models that could explain these results. The first thing we tried was to let theta>1 in the aDDM. This managed to fit choices, response times, and attentional choice biases well. However, letting theta grow above 1 loses intuitive interpretation of theta, so we’ve moved this to the appendix. See Appendix for why (talk about Bayesian models like Jang et al., 2021 and Callaway et al., 2021). First, the additive model of attention (AddDDM) always adds an attentional constant in favor of the attended option, which could predict our attentional choice bias results. Second, a reference-dependent aDDM (RaDDM) that transforms negative value signals to positive signals is also capable of explaining our results. The original aDDM and the ``goal-relevant’’ model proposed in Sepulveda et al. (2020) are both nested in the RaDDM.

We did some model comparison using posterior model probabilities, but both the AddDDM and RaDDM do a decent job in fitting our behavior. Even if one model looks like it performs slightly better than the other on average, we have no formal threshold to claim one is better-fitting than the other. The fact that they both perform well is not surprising, given that both models have previously done well to capture the speed-accuracy trade-off (Cavanaugh et al., 2014; Krajbich et al. 2010). Instead than relying on posterior model probabilities for selecting a model, we take advantage of a behavioral signature in our data to distinguish the models. Smith and Krabjich (2019) used the relationship between response times (RT) and overall value (OV) to distinguish between the aDDM and AddDDM in choices between gains. We can look at this same relationship in choices between losses to distinguish the aDDM, AddDDM, and RaDDM since each model makes a different prediction: [a] the aDDM predicts RT(OV) is increasing; [b] the AddDDM predicts it is flat; and [c] the RaDDM predicts it is decreasing. We use the same regression test as Smith and Krajbich (2019) and find that in both studies, RT(OV) is significantly decreasing in the loss condition. This suggests that participants are using a data-generating-process similar to the RaDDM.

Model-Based Results

We fit the RaDDM to our participants using odd-numbered trials (training data) and compare parameters across conditions, both at the group-level and individual-level. At the group-level, drift rate was slightly smaller in the gain condition in Study 1, suggesting that participants may have been slightly more efficient at distinguishing red-and-white dots than green-and-white dots. In Study 2, drift rate was slightly smaller in the loss condition, which is consistent with observed response times and self-reports from participants that they found it slightly more difficulty to comprehend negative-outcome lotteries than positive-outcome lotteries. Noise, starting-point bias, and attentional bias did not exhibit any meaningful differences between the two conditions. This is consistent with our observed attentional choice biases, which also did not exhibit any significant differences between the two conditions. *I am currently working on analyses of the free reference-point. So far, it seems to be below the minimum value in a given context, suggesting that people are accumulating strictly positive, reference-dependent value signals.*

Comparing our group-level, averaged estimates with the individual-level estimates, we can see that our results are not driven by outliers or multi-modal distributions of estimates (which would invalidate our analysis of the group-level averages).

Lastly, as a posterior predictive check, we ran out-of-sample simulations of choices, response times, last fixation bias, and net fixation bias for each participants using even-numbered trials. We found that predictions of the RaDDM qualitatively matched the out-of-sample data.

# Methods. Just list out the subsections I want to include. Details can come as I write the paper.

Participants

Procedures

Eye-Tracking (mention the PsychoPy timing correction)

Inference Strategy

Computational Model

aDDM Fitting

Out-of-Sample Simulations

Hierarchical Regressions

# Discussion. State my research question. Then go over my main results in one paragraph and answer how they address my research question. Then position these results in the literature. Then discuss next steps.

Summary

We wanted to understand attention in choices between losses. To do this, we ran two binary, risky choice studies with eye-tracking. Contrary to our predictions, we found identical attentional choice biases in gain and loss condition. To explain these results, we used a behavioral signature in the data to distinguish between different attentional choice process models. We found that the RaDDM best-explains the data. Even in choices between losses, people are accumulating positive, reference-dependent value signals. This finding explains the identical attentional choice biases that we found in both conditions and suggests a different interpretation of the evidence that we accumulate during our decisions than the aDDM.

Placing Our Results in the Literature

Our interpretation of the evidence is similar to the ``goal-relevant’’ evidence suggested by Sepulveda et al. (2020). However, unlike Sepulveda et al., we allow the reference-point to be a free parameter rather than enforcing a prespecified reference-point. This allows us to ask if ``goal-relevant’’ evidence is strictly positive. Our results suggest that most individuals are sampling strictly positive information about value, even in choices between losses. This result is aligned with Kim, Shimojo, and O’Doherty (2006), who find that avoiding aversive outcomes is encoded as a positive reward in the mOFC.

Talk about reference-dependence in the brain. vStr and value encoding. Range normalization in the OFC as a form of reference-dependence. Unfortunately, range normalization is not identifiable in the aDDM since the denominator (range) of the value signals factors out and influences the drift rate. This means a range-normalized aDDM is indistinguishable from a reference-dependent aDDM with the reference-point set to the minimum value and a smaller drift rate.

Future Directions

There is heterogeneity amongst individuals about ``how’’ positive their reference-dependent signals are. In the future, it may be interesting to if there are correlations between reference-point estimates and disorders (like anxiety and depression) or states (like hunger and thirst).

Another potential use of the free reference-point parameter in our model is to identify reference-points in certain markets or situations. In economics, reference-dependent models of choice are capable of explaining a variety of behaviors; however, they suffer from an estimation problem (Sprenger and O’Donohue, 2018). Each scenario requires a unique approach for suggesting and testing a proposed reference-point, making it difficult to apply reference-dependent models freely (Camerer, Babcock, Lowenstein, and Thaler, 1997; Fehr and Goette, 2007; Allen, Dechow, Pope, and Wu, 2017; Pope and Scheitzer, 2011; Rees-Jones, 2018; Barberis and Xiong, 2012; List, 2002; DellaVigna et al., 2017). Eye-tracking data combined with the choice process modelling proposed in this paper could offer a standardized approach to estimating reference-points in any scenario.

# Go back to the Intro. Now how would I introduce the paper? What is known about your research question so far? Summarize what I plan to do, then preview the results.

Why should we be interested in how attention affects choices between losses? Maybe some statistics about crappy choices that people have to make, like debt and healthcare? Can I get away with a NYT comic strip?! (I can purchase the license for publication.)



Talk about how attention affects choices in general. All the Krajbich papers. Tavares paper. But these are all in gains.

There’s also some papers on multi-attribute attention in risk choices. Mention Fiedler and Glockner (2012) and the other papers from your last SDN proseminar presentation. None of these were explicit choices between negatively-valued options, and the results about the role of attribute attention were mixed.

Some stuff about aversive choices, but nothing to do with attention. I gotta do some reading here. Probably gonna be related to papers about loss aversion, which then ties the intro to literature on reference-dependence too. A bit of foreshadowing without saying what we’re doing in our model. Maybe we address some disappointment aversion by Loomes and Sugden (1986) or expectations-Based reference-points by Koszegi and Rabin (2006; 2009a). I think Charlie has a paper that argues KR over Loomes and Sugden (Sprenger, 2015).

Mention Armel, Beaumel, and Rangel (2008), but describe how it is with forced fixations and sequential display. Both of these properties of their experiment would bias their results towards the predictions of the aDDM, which is meant to be a choice process model of choices with free response time. Mention Basu and Savani (2017, 2019) for sequential presentation.

# Now give the paper a title and summarize it in an abstract.

Abstract

Intro

Literature

Model-Based Hypotheses

Results

Paradigm

Basic Psychometrics

Fixation Process

Attentional Choice Biases

Diffusion Modeling

Reference-Dependent aDDM (RaDDM)

Rt(oV) behavior suggests RaDDM over aDDM

Report results

Discussion

Methods

Participants

Procedures

Eye-Tracking (PsychoPy timing correction)

Inference Strategy

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Acknowledgements