**Claim 1: The model-based analyses in the paper should be based on the RaDDM.**

**Claim 2: We should be testing reference-points below the minimum value in a context, especially in losses. Maybe not so important in gains.**

**Claim 3: We should make reference-point a free-parameter in the RaDDM.**

Evidence for why I think we should do this

**Evidence for Claim 1.** Of course I show posterior model probabilities, but there’s no threshold for a better-fitting model. Also, no model seems to be an obvious winner, likely because they’re all capable of accurately predicting choices, rts, and attentional biases out-of-sample. Instead, I got an idea for a test of behavior that is different across all the models. Smith and Krajbich (2019) run the regression below to test the relationship between response times and overall value. They use this to distinguish between a multiplicative and additive model of attention.

A black text on a white background

Description automatically generated

This is perfect for us too. In losses, the aDDM predicts a positive and significant beta\_2. The AddDDM predicts an insignificant beta\_2. The RaDDM predicts a negative and significant beta\_2. I have simulations showing this in the supplementary of the paper. Turns out, we see a negative and significant beta\_2 in our data! I think this is enough for me to say that we should use the RaDDM for the model-based analyses.

A table with numbers and text

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**Evidence for Claim 2.** I made a mistake when fitting Study 1 and used the reference points from Study 2 (Study 2 was fitted correctly). In gains, this made the reference point significantly lower in than the minimum value (ref pt = min - 3.5; scale from 4.5 to 5.5). In losses, this made the reference point slightly below (ref pt = min - 0.5; scale from -5.5 to -4.5). This mistake had noticeable effects on model performance in Study 1.

A group of red and green boxes

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Notice that the RaDDM performs as well as, if not better, than the aDDM on average across participants in gains. But in losses, it performs worse than the aDDM (and even the AddDDM) on average.

I think this matters a lot in Study 1 since there are a lot of trials where subjects may encounter a lottery with the minimum value. This means they are encountering a non-negligible number of trials where the ref-dept value signal for one of the options is 0, so no amount of fixating on it will lead them to choose it (ignoring noise). I think this is going to severely hurt the fitting, especially in a perceptual task. I thought that letting the lower bound on theta go below 0 might help fix this (leaky aDDM), but the RaDDM was by far the worst fitting model still.

In Study 2, values are bounded between 1 and 6 (-6 and -1 in losses), but subjects HARDLY ever encounter the minimum possible value. Therefore, it’s almost always the case that subjects are accumulating over STRICTLY positive reference-dependent value signals, so setting the reference-point to the minimum value isn’t hurting fits that much.

Lastly, I actually did properly fit the RaDDM with the reference-point = minimum value in Study 1. The RaDDM was almost always the least likely model of the 3 in Study 1.

**A group of diagrams showing different types of data

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I think part of the reason it fit so poorly was that drift rates were larger than what I had in my grid (ref-dept values are smaller, so evidence is smaller, so drift needs to grow BY A LOT to compensate). Because drift rate was capping, I think the model was trying to further speed up the decisions my minimizing theta (therefore making evidence as large as possible). Many of the theta estimates were at 0. See figure below.

A group of graphs showing the results of a loss

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I tried refitting but allowing the drift rate to grow A LOT larger. Drift rates went up 2-fold or more, but theta did not move. Again, model posteriors looked bad.

Retrying this on a few subjects that had theta clipping at 0, but letting the reference point be minimum value – 1, I got drift rates that were still a bit larger than before, but theta is no longer clipped to 0 and is instead acting reasonably (around 0.5). See screenshot below.

A screenshot of a computer

Description automatically generated

Model posteriors also look more promising. Ignore formatting, it’s a screenshot from RStudio.

A diagram of a model

Description automatically generated with medium confidence

**Evidence for Claim 3.** I have no reason to say that we should set reference point to minimum value – 1, or any other value for that matter. But I do think people are accumulating STICTLY positive reference-dependent value signals, since I think people are asking “Why should I pick this option?” when they look at something. I don’t want to impose a reference-point, but instead I’d like to let it be a free parameter in the model, where we’re testing values near the minimum possible value, as well as, 0. This means the RaDDM will always have at least one set of parameters that fits at least as well as the aDDM.

I was worried this would not be identifiable, since the free reference-point is also going to affect the size of theta. BUT, somehow (and I’m still trying to wrap my head around this), the RaDDM with free reference-point performs VERY WELL with parameter recovery. See the new model recovery figure and 20 simulations of the RaDDM in gains + losses in the parameter recover report.

Reasons why making reference point a free parameter makes the paper stronger

It conceptually distinguishes us from the Sepulveda et al (2021) paper.

It nests the original aDDM (reference-point = 0).

It introduces a potential way to measure reference points using attention. Perhaps this could be used to solve the problem of arguing a reference-point in economics. Could be interesting to go back to previous studies and verify if the fitted reference-point using RaDDM matches the reference-point argued by previous authors in X market.