Supporting Information

1. **DDM with interactions between incentives and trial congruence**

We performed additional model comparison regarding the necessity of adding

interaction between incentives and trial type into the DDM analysis (Figure A1A). The

best one includes an interaction between penalty and trial type for both drift rate and

threshold. When looking at the interaction between penalty and trial type, we found

significant effects on drift rate in both studies. In Study 1, we found that higher penalty

increases the drift rate on incongruent trials but marginally decreased drift rate on

congruent trials (Figure A1B). The interaction between penalty and congruence for drift

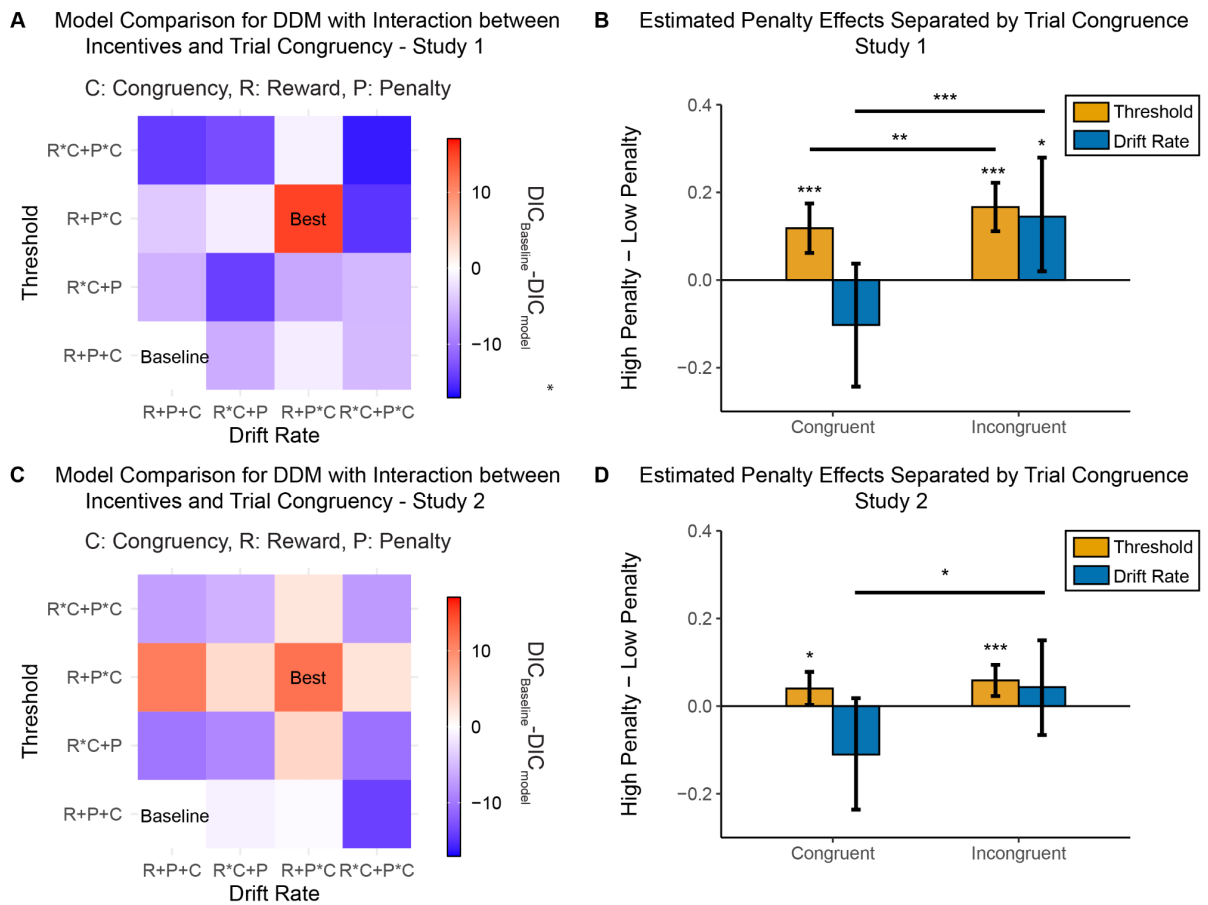rate in Study 2 follows the same direction in Study 1 (Figure A1C-D).

Figure A1. Drift diffusion model with interaction between incentive level and trial congruence. Model comparison based on DIC shows that the best model for Study 1 includes interaction between penalty and trial type for both drift rate and threshold **(A)**. The estimates of penalty effects separated by trial type in Study 1 is shown in **(B)**. Model comparison confirmed that the best model for Study 2 takes the same structure **(C)**. The estimates of penalty effects separated by trial type in Study 2 is shown in **(D).** Error bars reflect 95% CI. *: p<0.05; ***: p<0.001.

2. Alternate effort cost functions for drift rate and threshold

We considered linear, quadratic and exponential functions for effort cost of drift rate (denoted as v):

$$Linear, drift\ rate\ only: Cost \sim v$$

$$Quadratic, drift\ rate\ only: Cost \sim v^2$$

$$Exponential, drift\ rate\ only: Cost \sim e^v$$

The reward rate models with linear and exponential cost functions predict a discontinuity in the relationship between reward and drift rate (Figure A2A). This prediction is due to the bimodal profile of the reward rate function with these two alternatives, and the presence of a transition between modes when reward increases (Figure A2B). Based on these considerations and previous support for quadratic effort costs [1–5], we decided to use the quadratic function for our key model simulations. Critically, none of our predicted incentive effects differ substantially under either of these alternate effort cost functions.
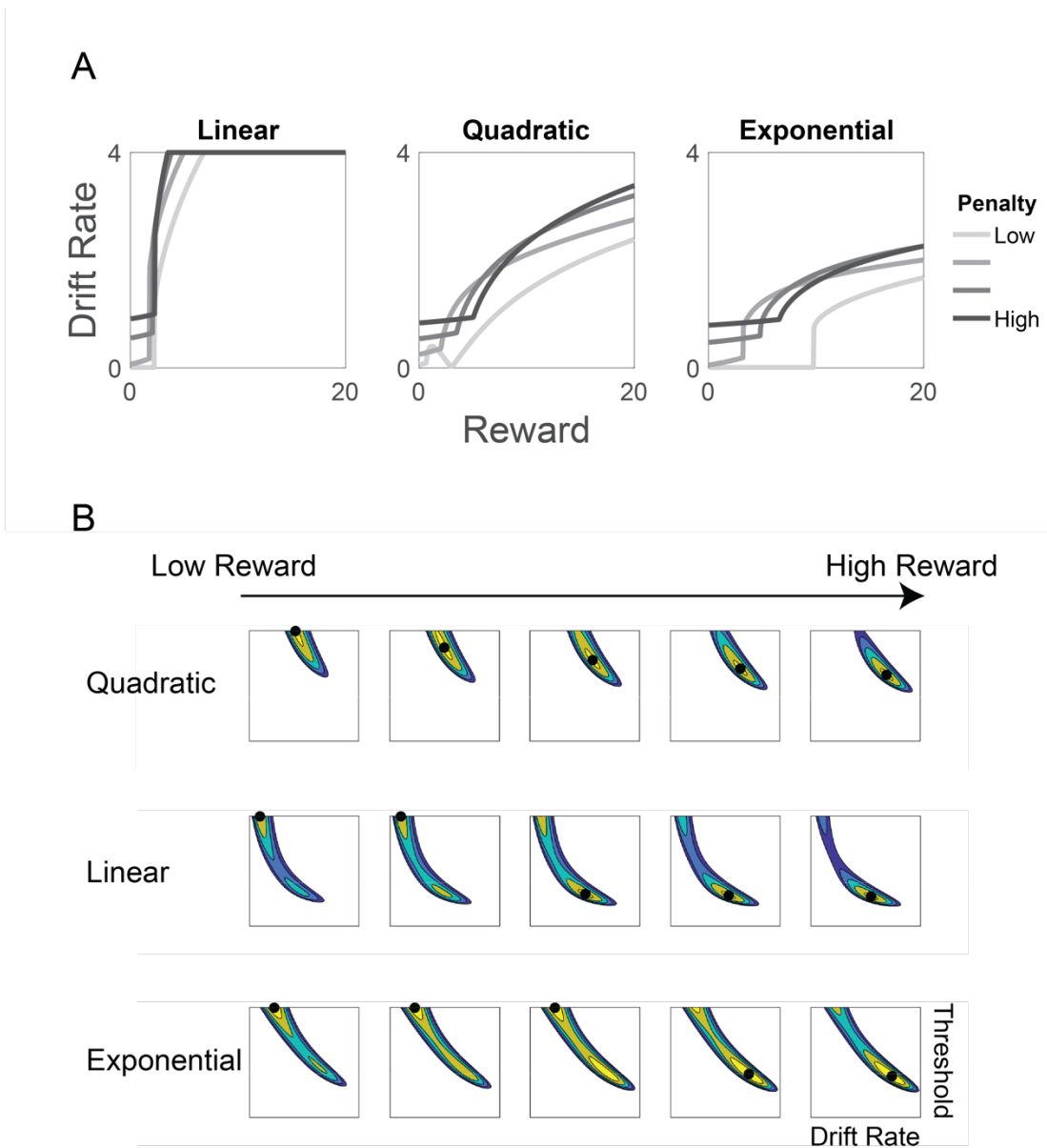
Figure A2. Predicted relationship between reward and optimal drift rate with different format of effort cost. Both linear and exponential formats of effort cost predict step function in the relationship between reward and optimal drift rate **(A)**. This is due to the existence of bimodality in the objective function **(B)**. A small increase of reward is associated with a shift of the optimal configuration of drift rate and threshold between the two modes.

We also considered the possibility that threshold (denoted as a) carried an effort cost rather than omitting such a cost (as in our prediction in the main text):

$$Quadratic, drift\ rate\ and\ threshold: Cost\ \sim v^2 + a^2$$

We simulated how drift rate and threshold would jointly vary as a function of reward and penalty, both with and without an assumed threshold cost (in both cases assuming that drift rate carries a quadratic cost). The predictions of these two models were qualitatively very similar (Figure A3A-B), largely because threshold already carries a time cost for slower responding. The only distinguishing feature between these was the prediction of increased drift rate with higher penalties when assuming a cost for threshold (because these costs now trade off against the cost on drift rate), a prediction that our studies are unable to conclusively support or refute (Figure A3C). In the absence of clear evidence for this distinct prediction, we opted to omit a threshold cost for our main model simulations for the sake of parsimony but, as with alternate drift rate cost functions, none of our key conclusions would change under this alternative.
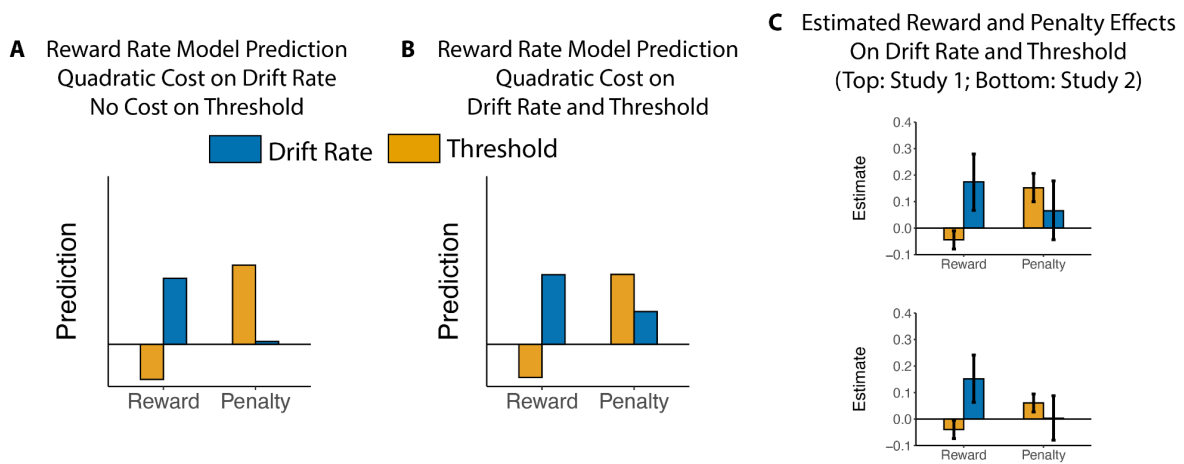
A Reward Rate Model Prediction
Quadratic Cost on Drift Rate
No Cost on Threshold

B Reward Rate Model Prediction
Quadratic Cost on
Drift Rate and Threshold

C Estimated Reward and Penalty Effects
On Drift Rate and Threshold
(Top: Study 1; Bottom: Study 2)

Figure A3. Predicted incentive effects with and without effort cost of threshold. The predicted reward and penalty effects on drift rate and threshold from reward rate model without cost on threshold **(A)** and with cost on threshold **(B)** are qualitatively consistent. The estimated reward and penalty effects in the current data **(C; adapted from Fig 4 and Fig 6)** do not provide strong evidence regarding whether the cost of threshold should be included in the model. Error bars reflect 95% CI.

3. Model comparisons to DDM's with task-modulated non-decision time

In addition to the models estimated in Figure 4, we also considered models that estimated parameters for reward and penalty influences on non-decision time (NDT). Based on the best model shown in Fig 4B, we performed additional model comparison (Figure A4A). In the best model, we found a significant effect of penalty on NDT (Figure A4C). The best model with NDT maintains the same patterns of incentive effects on drift rate and threshold estimated in Fig 4, so that the findings in the paper are not due to incentive effects on stimuli encoding and/or motor responses. Based on these results, we did not include models with NDT in the paper.
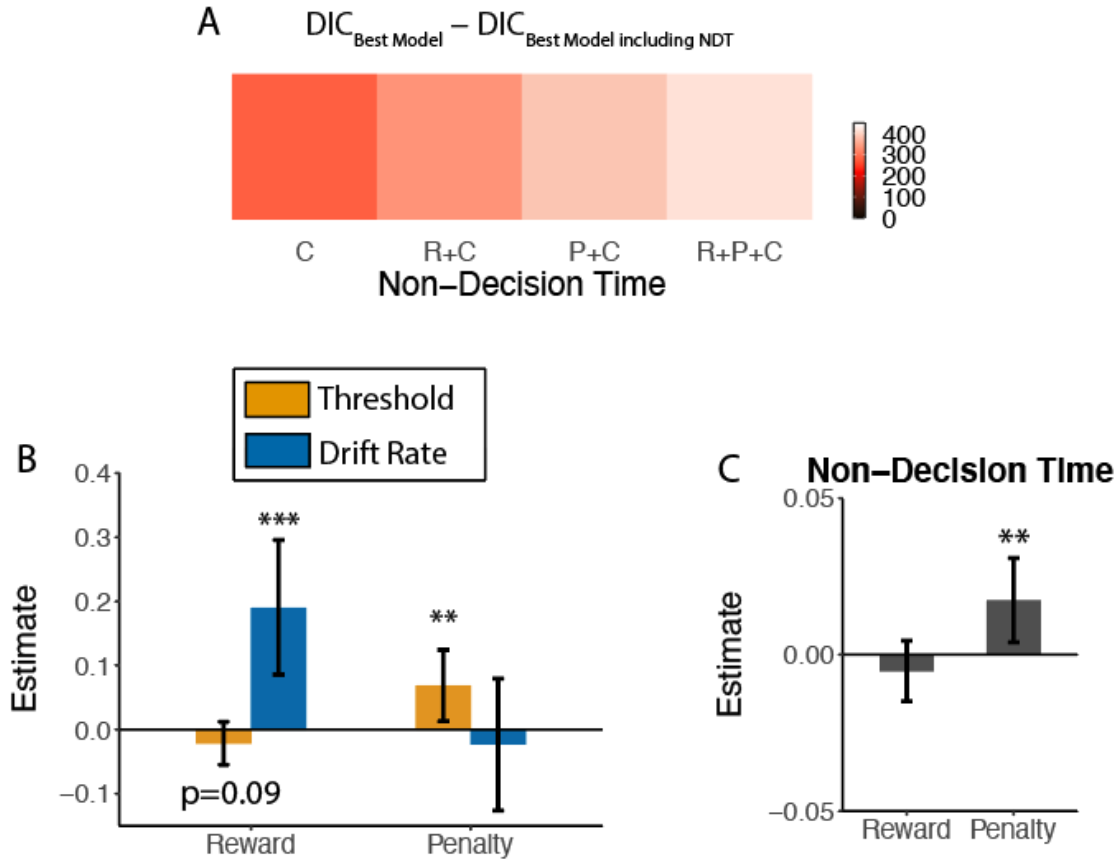
Figure A4. Model comparison between best model in Figure 4B and models including non-decision time (Study 1). A) The best model includes all predictors (reward, penalty and stimuli congruency) for non-decision time. **B)** Estimated effect of reward and penalty on threshold, drift rate and non-decision time for the selected model from Figure A2A. The patterns in threshold and drift rate are consistent with the best model in Figure 4B. **C)** There is a significant effect of penalty (but not of reward) on non-decision time. Error bars reflect 95% CI. **: $p<0.01$; ***: $p<0.001$.

4. Posterior predictive check for Drift Diffusion Model (DDM)

We performed a posterior predictive check for the fitted Drift Diffusion Model (DDM). We generated 500 independent samples from the posterior distribution of fitted parameters and then simulated the reaction time distribution for each posterior sample. The predicted reaction time distribution matches with the actual reaction time distribution for each condition (Figure A5).
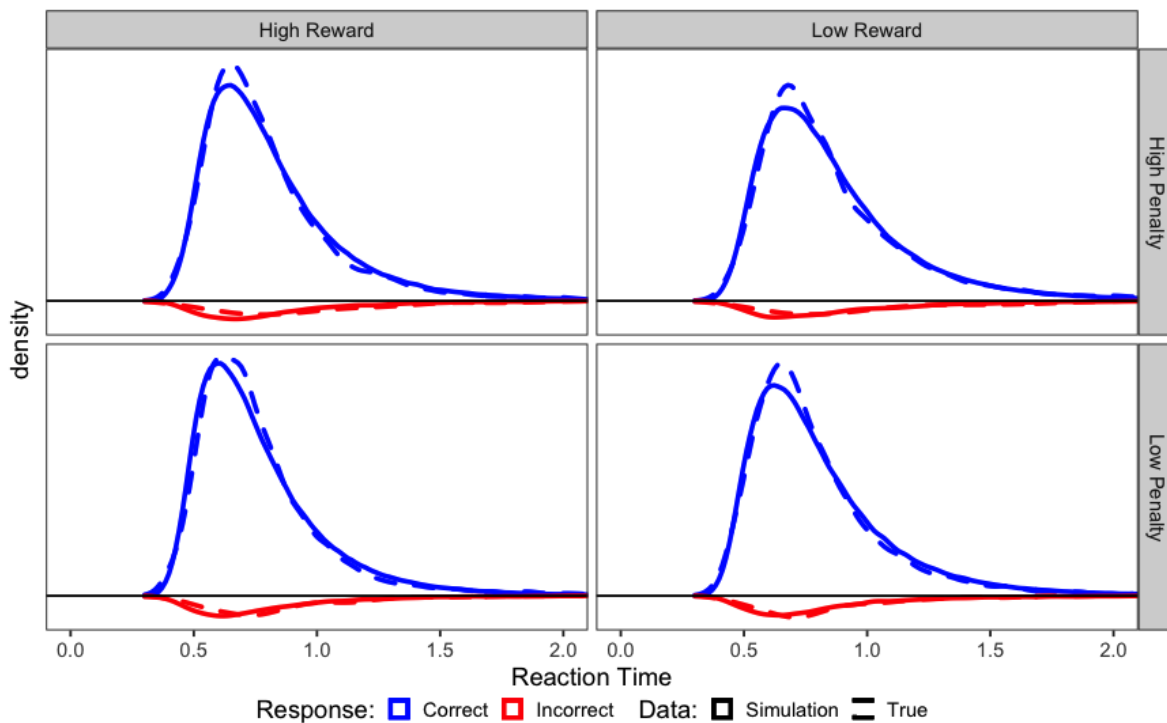

Figure A5. Posterior predictive check for DDM (Study 1). For each condition, the distribution of simulated reaction time from posterior predictive check (solid line) matches with the actual reaction time distribution (dashed line) for both correct and incorrect responses.

5. Parameter recovery for subjective weights of reward and penalty

We performed simulation-based parameter recovery for subjective weights of reward and penalty. To cover the range of inferred reward and penalty values, we sampled uniformly in (4,10) and (10, 70) independently for reward and penalty to create 100 pairs of reward and penalty values. The non-decision time for each pair of reward and penalty is sampled uniformly in (0.35, 0.45) For each pair of reward and penalty values, we find the optimal drift rate and threshold that optimize the reward rate. We then generate 2000 trials for each pair of reward and penalty. By fitting the distribution of reaction time and accuracy with drift diffusion model, we estimate the drift rate, threshold and the non-decision time. Using these estimated parameters, we performed the inverse reward-rate optimization to infer the reward and penalty values (Figure A6). Both reward and penalty can be recovered from the inverse reward-rate optimization process.
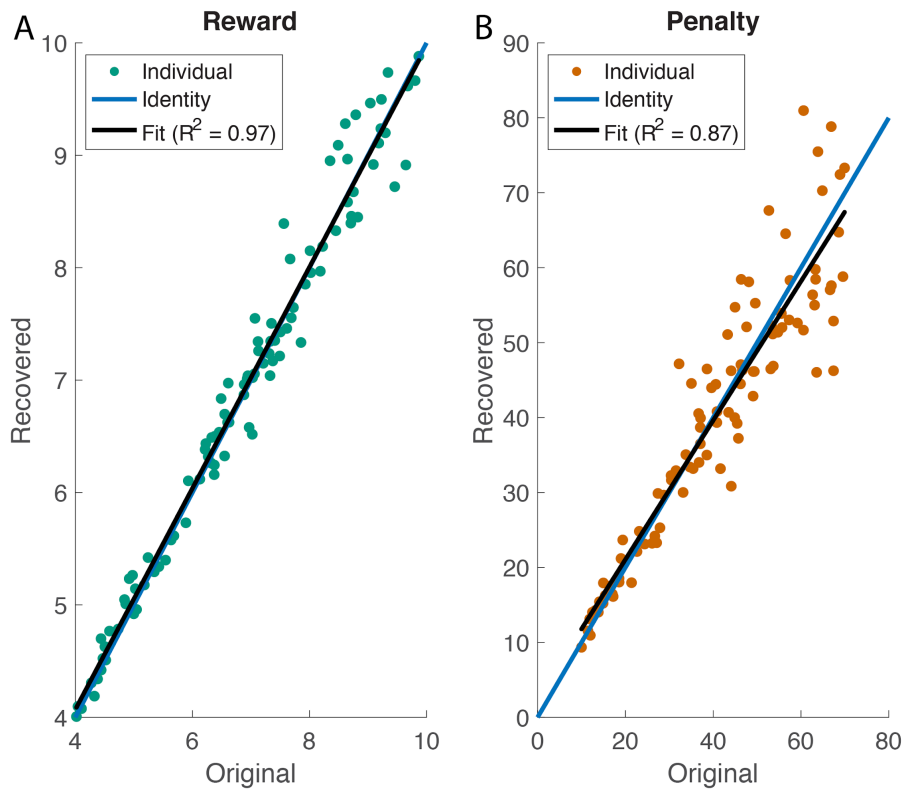
Figure A6. Parameter recovery for the subjective weights (Study 1). A) recovered reward versus original reward. **B)** recovered penalty versus original penalty. Both reward and penalty can be recovered from the inverse reward-rate optimization process.

6. Mixed model Results for behavioral data from Study 2

Table A1 and A2 show the details of the fitted mixed models for response rate, reaction time and accuracy.

Table A1. Mixed Model Results for Correct Responses per Second

(Study 2)

*: $p<0.05$, **: $p<0.01$, ***: $p<0.001$

Predictors	Correct Responses Per Second		
Predictors	*Estimates*	*S.E.*	*P-Value*
Age	-0.005	0.028	0.849
Female - Male	-0.025	0.028	0.368
Medium Reward - Low Reward	0.050	0.010	**<0.001*****
High Reward - Medium Reward	0.009	0.007	0.244
Medium Penalty - Low Penalty	-0.019	0.008	**0.018***
High Penalty - Medium Penalty	-0.008	0.008	0.302
Average Congruence	-0.005	0.004	0.234
Number of Subjects	65		
Observations	4429		
Marginal R^2 / Conditional R^2	0.017 / 0.678		

Table A2. Mixed Model Results for Log-Transformed Reaction Time and Accuracy

(Study 2)

*: $p<0.05$, **: $p<0.01$, ***: $p<0.001$

Italic: does not reach threshold of significance but is trending

	Log-transformed RT			Accuracy		
Predictors	*Estimates*	*S.E.*	*P-Value*	*Odds Ratios*	*S.E.*	*P-Value*
Age	0.010	0.011	0.355	1.109	0.084	0.173
Female - Male	0.015	0.010	0.162	1.090	0.083	0.257
Medium Reward - Low Reward	-0.013	0.003	**<0.001***	0.954	0.079	0.568
High Reward - Medium Reward	-0.004	0.002	*0.056*	0.909	0.070	0.216
Medium Penalty - Low Penalty	0.007	0.002	**0.002**	1.070	0.090	0.419
High Penalty - Medium Penalty	0.005	0.002	**0.042***	1.296	0.109	**0.002**
Trial Congruence (Cong-Incong)	-0.015	0.001	**<0.001***	1.094	0.045	**0.030***
Number of Subjects	65			65		
Observations	35358			36627		
Marginal R^2 / Conditional R^2	0.030 / 0.462			0.014 / 0.112		

7. Drift diffusion model results for Study 2

We fit the behavioral performance (reaction time and accuracy) in Study 2 with the HDDM with the selected model from Study 1. We found that drift rate increased with larger rewards (low to medium and medium to high), and threshold increased with larger punishment (medium to high). These results are consistent with normative prediction and previous findings in Study 1 that reward and punishment exhibited dissociable influences on drift rate and threshold.
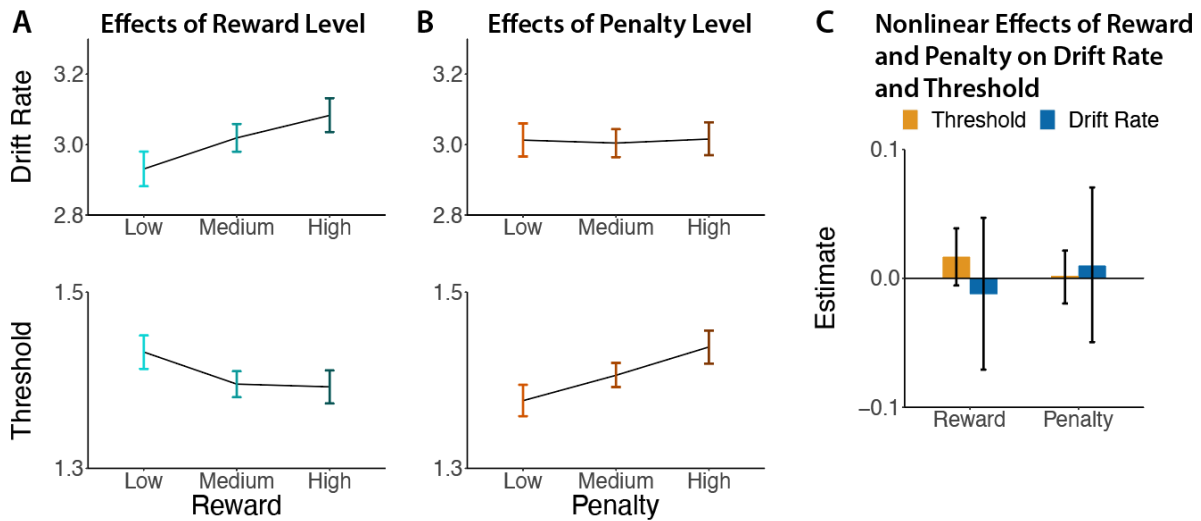

Figure A7. Empirically observed estimates of incentive effects on DDM parameters in Study 2. We found that **(A)** larger expected rewards led to increased drift rate whereas **(B)** larger expected penalties led to increased threshold, and that **(C)** no significant nonlinear effect of reward or penalty on DDM parameters. Error bars reflect 95% CI.

References

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