Reducing Modest Risks: Valuation or Disposition?
Online Supplemental Material

Research Transparency

No aspects of Study 1 were preregistered. The hypotheses, methods, and analysis plan for Study 2 were preregistered (`https://osf.io/9ymt7`) on Nov 13, 2023, prior to data collection which began on Nov 13, 2023. There were no deviations from the preregistration. All primary data and analysis scripts for both studies are publicly available. Repository: `https://osf.io/mgw9c`

Power Analysis

Prior to data collection, we arranged a pilot study with the same method and materials as in Study 1, using 6 subjects from the Prolific platform. We tested how framing affects their probability of choice of RRO using a generalized linear mixed model with the logistic link function. This test was conducted to probe for magnitude of the nested random effects, which were $SD = 1.31$ for the nested trial/subject random effect, and $SD = 0.41$ for subject RE. These figures were used as a basis for the power simulations.

We then used power simulations with the r-simr package[1]. To start, we extended the pilot data artificially to 100 subjects and were interested to find the smallest effect sizes of interest on given power levels with this sample size. The power simulations used alpha level of 0.05 and conservative random effects informed by the pilot study results. Using the simulations we found that there is an 84% statistical power (95% CI = $[75.3, 90.6]$) to detect a decrease of 15% in the probability of choosing the RRO (i.e. log-odds $\log(0.85)$). This effect size is relevant for Study 1 as we expected the probability of RRO choice to decrease when moving from explicit to implicit framing. For the time pressure framing of Study 2, we expected the probability of RRO choices to increase, therefore we found that there is an 88% power (95% CI = $[79.9, 93.6]$) of detecting a 20% increase (log-odds $\log(1.2)$) in RRO choice frequency. A larger framing effect is expected under time pressure; e.g. Guo et al. (2017) report that 63.5% of the variance in choice is explained by time pressure, which implies an effect that expressed in log-odds is higher than $\log(2)$.

We then turned to investigating statistical power for detecting framing differences (smallest effect size of interest) in drift rate μ using a linear mixed model. We first estimated the hierarchical DDM for the pilot subjects similarly as in the main studies (see section Hierarchical DDMs later in this document). This informed us of the distributional structure for μ which had to be simulated in the 100 subject dataset. Then we found using the power simulation that a slope $= -0.005$, i.e. a 0.5% decrease in μ due to framing, gives 93% statistical power (95% CI = $[86.1, 97.1]$.

[1] Version 1.0.7, `https://CRAN.R-project.org/package=simr`

Response Times Over Time

Figure S1 plots log-transformed response times as function of round number in Study 1.

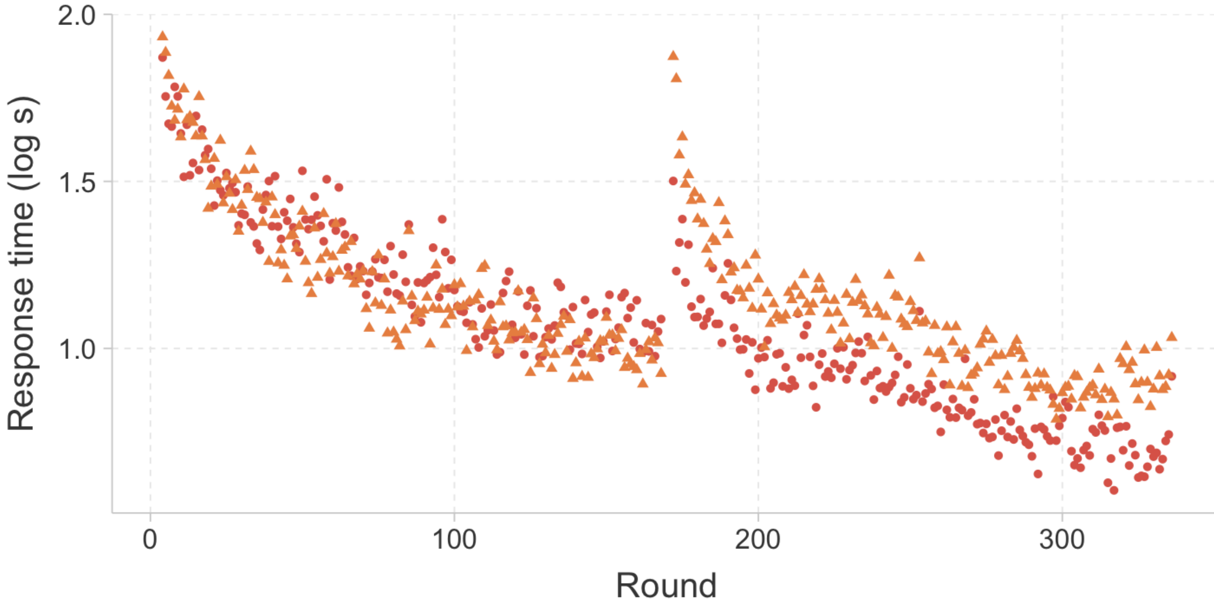

Figure S1: Response times as function of round number in Study 1. Filled triangles = implicit frame, solid circles = explicit frame.

Model Fit

In Figure S2 we report model fit plot using the main GLMM models that predict choice of the RRO, for both studies. We plotted the mean observed choice probability for each unique trial against the corresponding predicted probabilities from the fitted GLMM. The observed choice probabilities were computed by averaging binary choices across subjects for each gamble. The model predictions were obtained using the fitted logistic GLMM, and represent point estimates (i.e., the expected probability of choosing the option, conditional on the fixed and random effects structure).

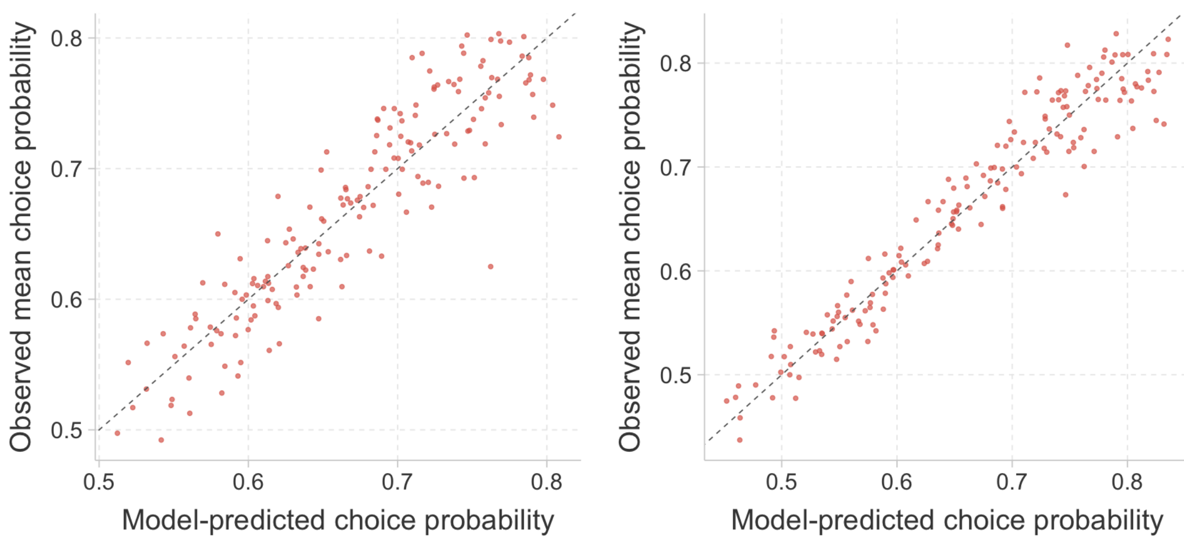

Figure S2: GLMM Fit Comparisons for Study 1 (left) and Study 2 (right)

Additional Details on the DDM

Simulated Probabilities and Response Times

We show that the estimated DDMs can simulate the probability of choosing RROs and RT percentiles for each subject in each frame with high accuracy. Simulated choice probabilities were computed directly from the estimated models. To obtain simulated RT percentiles, 1,000 simulated trials were generated for each real decision trial using the DDM parameters estimated from the observed data. From the simulated decision trials of each subject, we extracted RTs at the 10th, 30th, 50th, 70th, and 90th percentiles and compared them to the corresponding percentiles from the observed data. Scatter plots of these comparisons for Study 1 and Study 2 are shown in Fig. S3 and S4, respectively, and the collapsing boundary DDM for Study 2 is shown in Fig. S5. Additionally, to provide a unified view of RT distribution comparisons, we generated percentile curve plots for both studies, illustrating the close correspondence between observed and simulated RT percentiles. These results are shown in Fig. S6. In all scenarios, we found near-perfect correlations between the observed and simulated statistics for each subject. This result validates the estimated DDMs by showing that they capture important subject-level variation in the choice behavior.

Overall, simulation accuracy is slightly lower for longer RT percentiles than for shorter ones. This pattern is consistent with previous findings that the DDM tends to be less accurate in accounting for long RTs (e.g. Ratcliff and Tuerlinckx, 2002). Notably, the DDM with collapsing boundaries provided more accurate simulation of long RT percentiles than the DDM without collapsing boundaries. This aligns with the model comparison results, which suggests that the DDM with collapsing boundaries provided a better fit to the decision making data for most subjects.

Cross-Validation

To evaluate how well the estimations predict out-of-sample choice observations, we performed cross-validation analyses in which we estimated DDMs for each subject in both studies using only the odd-numbered trials, following the same fitting procedure that was used for the full datasets. These odd-number trial estimations produced parameters ρ and β that were used in the RDEU model to calculate utility differences $U_{\text{RRO}} - U_{\text{non-RRO}}$ in even-number trials. We then determined whether the utility difference in each even-number trial of each subject corresponded to the choice that the subject made in that trial. A positive utility difference should predict choice of the RRO, and a negative utility difference should predict the choice of the non-RRO.

We calculated the percentage of trials of each correct prediction. In Study 1, the percentage of correctly predicted even-number trial choices is 79.6% in the explicit frame and 77.5% in the implicit frame. In Study 2, the corresponding numbers are 77.3% in the unrestricted frame and 79.4% in the time-pressure frame. We then averaged the percentage of correct trials over each subject and frame, and compared the difference in correctness between frames. In other words, we test whether subjects significantly vary in out-of-sample correctness between frames. In Study 1 the paired t-test result is not significant with mean difference 2.00% ($t = 1.43$, 95% CI = $[-0.0076, 0.047]$, $p = 0.15$), and in Study 2 the paired t-test result is likewise not significant with mean difference -1.99% ($t = -1.48$, 95% CI = $[-0.046, 0.0067]$, $p = 0.14$).

Parameter Recovery Analysis

To assess the validity of the estimated DDMs as descriptive models of decision making, we performed parameter recovery analyses. We compared the DDM parameters estimated from the observed data to those re-estimated from simulated data. Following the same simulation procedure used for generating RT percentiles, we generated 1,000 simulated trials per real decision trial using the DDM parameters previously estimated from the observed data. Parameters were then re-estimated from the simulated data using the same fitting procedure. We calculated Pearson's correlation coefficients between the original and recovered parameters to assess recovery performance. The results show that, across all frames and parameters, estimates from the observed data and those re-estimated from the simulated data are significantly correlated. However, a few parameters in certain frames exhibited relatively low correlations (e.g., < 0.3). A closer examination indicates that these lower correlations were primarily driven by a small number of subjects whose recovered parameter values differed substantially from their original estimates. We conducted an additional correlation analysis excluding the top 5% of subjects with the largest absolute differences between observed and recovered parameter estimates; this exclusion led to a notable improvement in the correlations. The results are summarised in Table S1. Overall, these findings suggest that the estimated DDM parameters are generally stable and provide a valid description of decision behaviour under investigation.

Table S1: Pearson's Correlation Coefficients Between Original and Recovered DDM Parameters

	d	ρ	β	B	x_0	t_0
Explicit + Unrestricted (195)	0.98	0.44	0.59	0.86	0.70	0.84
Implicit (95)	0.95	0.74	0.57	0.78	0.53	0.83
Time pressure (100)	0.98	0.72	0.72	0.73	0.69	0.79

Note: Top 5% subjects with the largest absolute differences between the estimates from observed and simulated data are excluded. Number of subjects in parentheses. Significance: all $p < .001$.

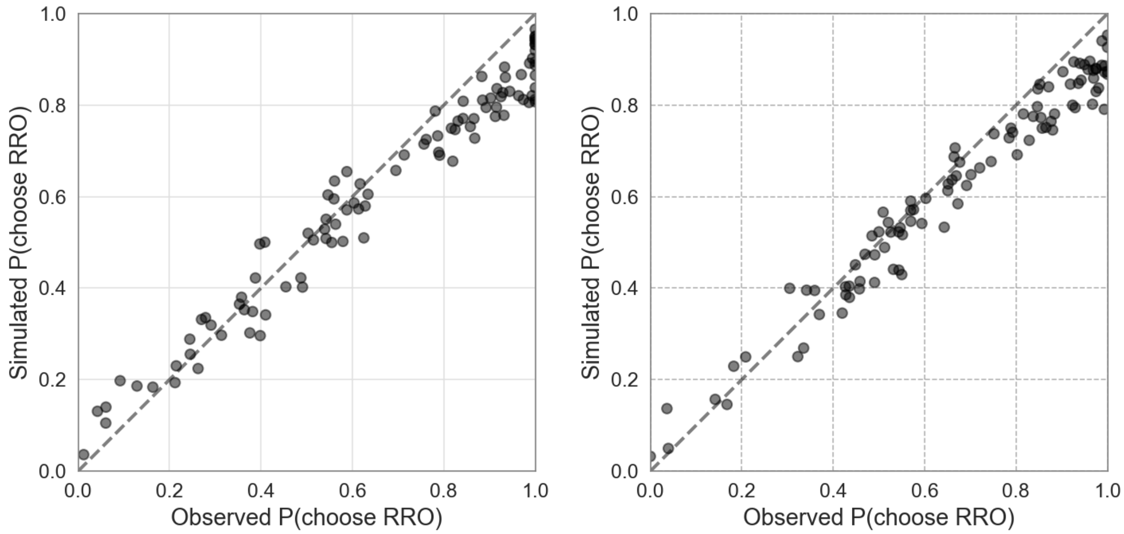

Figure S3: Scatter plots of actual and simulated choice probabilities in Study 1. Left = explicit frame, right = implicit frame. Pearson's correlation = 0.98 in both figures.

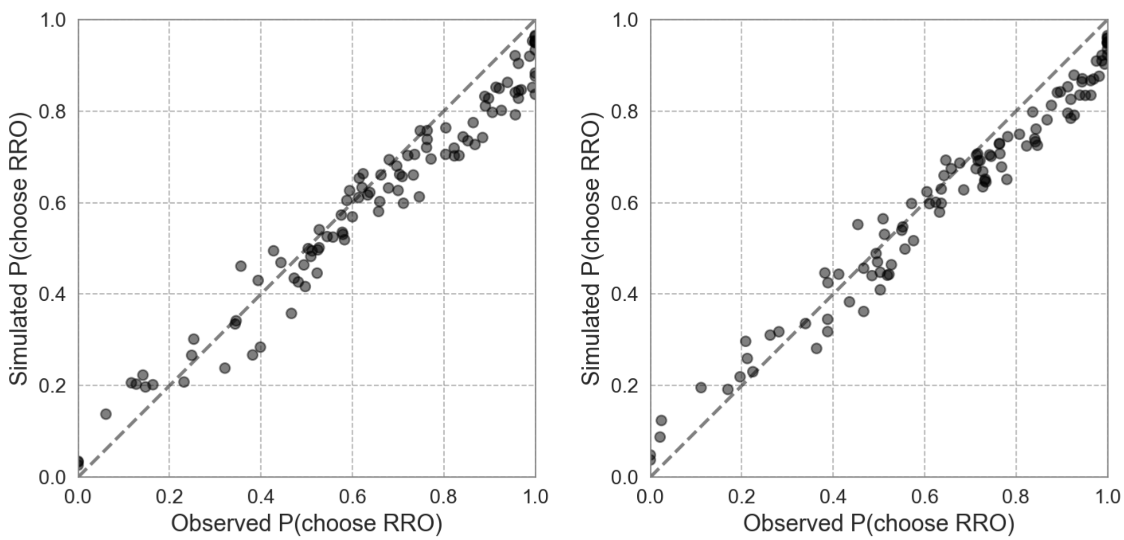

Figure S4: Observed vs. simulated probabilities in Study 2. Left = unrestricted frame, right = time-pressure frame. Pearson's correlation = 0.98 in both figures.

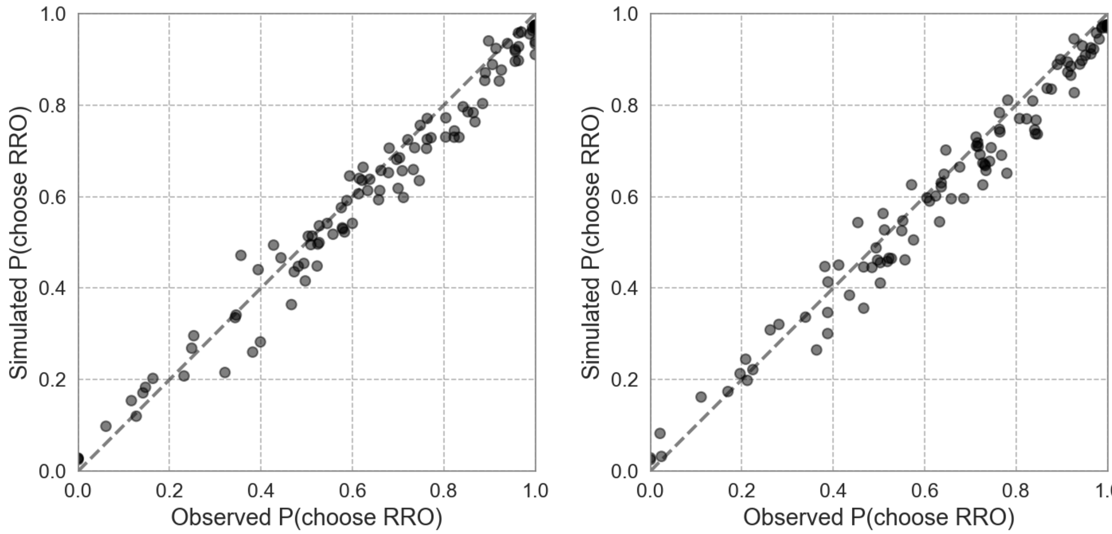

Figure S5: Observed vs. simulated probabilities in Study 2 for the collapsing boundary DDM. Left = unrestricted frame, right = time-pressure frame. Pearson's correlation = 0.98 in both figures.

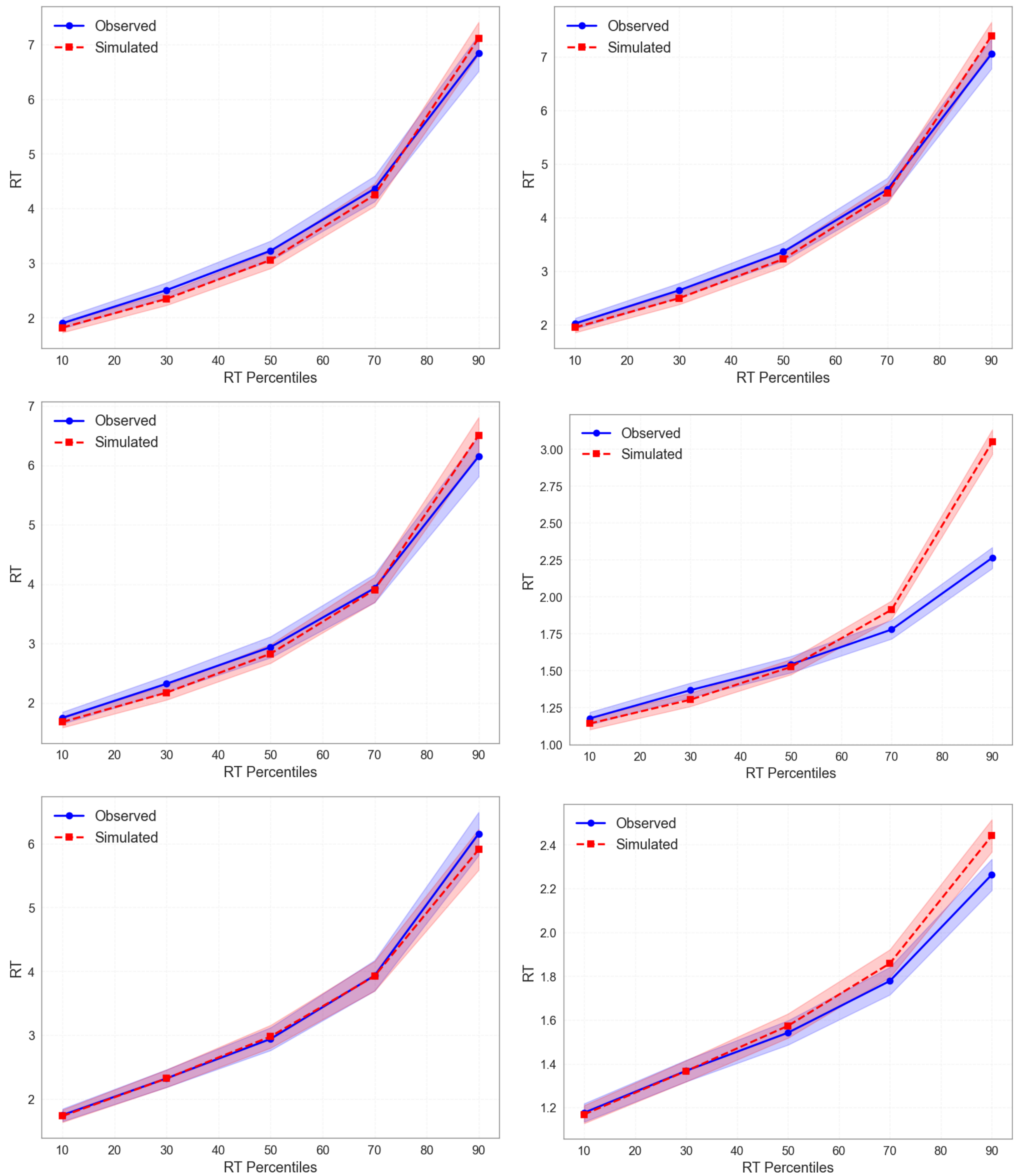

Figure S6: Percentile plots comparing observed and simulated response times. Top row: Study 1, explicit frame (left), implicit frame (right). Middle row: Study 2, unrestricted frame (left), time-pressure frame (right). Bottom row: Study 2 collapsing boundary DDM, unrestricted frame (left), time-pressure frame (right).

Response Dynamics Measurements

Illustration of the Method

Figure S7 illustrates the area-under-the-curve method for two example trajectories. The main text describes how the area under the curve is formed.

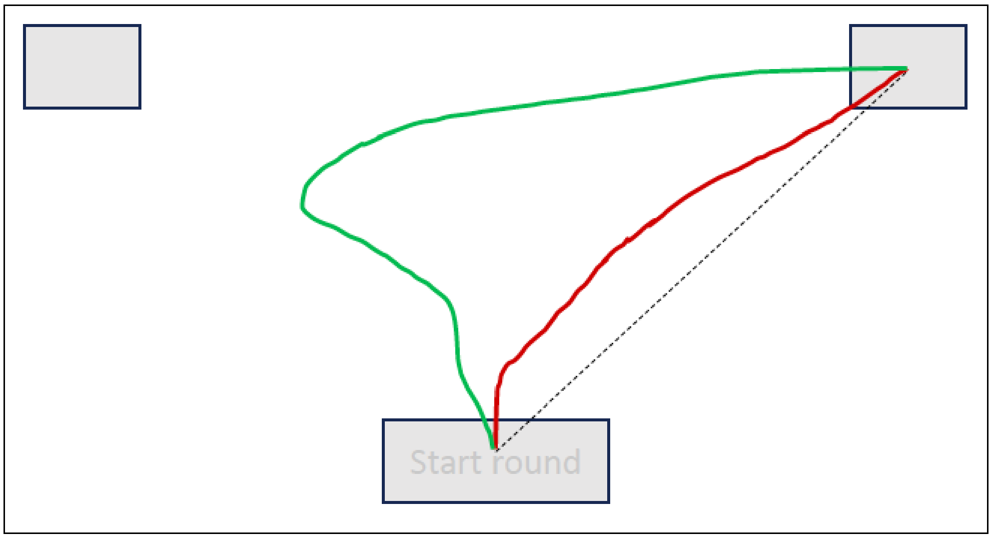

Figure S7: The response dynamics measurement. The trajectory of the pointer device, starting from the button that starts the round and ending to the choice button, is recorded, and the polygon area ψ is calculated as the area between the trajectory and a diagonal line (dashed) between the start and the chosen option. An ideal nonconflicted choice would follow the diagonal line. A larger ψ (green curve) reflects higher conflict and stronger pull from the nonchosen option in the preference formation process than a smaller ψ (red curve).

Exclusions

A total of 7 subjects in Study 1 and 10 subjects in Study 2 had corrupted response dynamics data, which we define as data where more than 10% of rounds do not have a complete trajectory recording and that is treated as missing values in the analyses. These subjects are excluded from the response dynamics analyses.

Study 1

To study how the dynamic preference formation process differs between frames, we use the mouse tracking metric ψ (area under the curve; see Study 1 method description) and estimate an LMM

$$\log(\psi) \sim \text{frame}, \qquad \text{for } \psi > 0 \tag{S1}$$

with subject id's as random effects. We find that the implicit frame has overall a significantly higher $\log(\psi)$ than the explicit frame (coefficient 0.14, 95% CI = $[0.11, 0.18]$, $p < .001$), suggesting that conflict is higher between the options during decision making when the RRO choice is framed implicitly. We can also use mouse tracking to predict RRO choice in each frame: using a GLMM

$$\text{choose RRO} \sim \text{frame} \times \psi \tag{S2}$$

with nested random effects and the logistic link function (main effects omitted), we find that while ψ does not predict choice in the explicit frame (interaction term odds ratio 0.99, 95% CI = $[0.95, 1.026]$, $p = .48$), it does so in the implicit frame (interaction term odds ratio 0.90, 95% CI = $[0.87, 0.94]$, $p < .001$). Hence, when the RRO choice is framed implicitly, higher conflict between the options is associated with lower log-odds of choosing the RRO, but when this framing is explicit, such a predictive relationship does not exist.

Study 2

Based on Study 1 results regarding how the conflict metric ψ predicts choice of RRO, we predicted that time pressure causes weakening of the preference formation process that is reflected in the amount of conflict between the options. We thus pre-registered the hypothesis that the probability of choosing the RRO decreases in ψ, but under time pressure this effect is weaker. Using the GLMM described in Eq. (S2), we find that in the unrestricted frame ψ predicts decreasing choice odds (interaction term odds ratio 0.76, 95% CI = $[0.72, 0.79]$, $p < .001$), in the time-pressure frame this effect is in fact stronger than in the unrestricted frame, contrary to the hypothesis (interaction term odds ratio 0.61, 95% CI = $[0.58, 0.64]$, $p < .001$). Thus, the tendency to choose the RRO is much more sensitive to ψ in the time-pressure frame than in the unrestricted frame. We also look at the aggregate ψ difference between frames (not pre-registered), and find that the time-pressure frame has overall a significantly lower $\log(\psi)$ than the unrestricted frame (Eq. S1; coefficient -0.15, 95% CI = $[-0.18, -0.11]$, $p < .001$). This result is in line with the μ difference between frames and further evidences that time pressure tends to decrease the competition between response options.

Hierarchical DDMs

To complement the primary DDM analyses reported in the main text, we also fit hierarchical DDMs for the data in both studies using Markov chain Monte Carlo (MCMC) sampling.[2] The hierarchical Bayesian model estimates a set of DDM parameters for each subject so that these individual parameters are governed by group-level distributions. The modeling approach allows hierarchical estimations where subjects enter the models as random effects. The hierarchical structure allows simultaneous estimation of subject and group parameters, where subjects are drawn from a common distribution. In both studies we used the following regression for μ (drift rate):

$$\mu \sim \text{frame} + U_{\text{diff}} \tag{S3}$$

where frame is coded 0 if explicit/unrestricted and 1 if implicit/time pressure, adding subjects as random effects. Here U_{diff} (see Methods of Study 1) is added as a covariate control. We also fit another hierarchical DDM without using utility difference

$$\mu \sim \text{frame} \times (L + P + \alpha). \tag{S4}$$

In both forms, parameters x_0 (DDM starting point), B (boundary separation) and t_0 (non-decision time) were treated as global parameters that did not experience subject-level variation. The continuous predictors of drift rate in Eqs. S3 and S4 were scaled and centered. All posterior samples were drawn from 4 chains with 10,000 draws and with 3,000 burn-in draws and non-informative prior distributions were wide. The scale reduction factor (Gelman and Rubin, 1992) was $\hat{r} \leq 1.01$ for all group-level parameters for all the DDMs, indicating that the chains had converged. Figure S9 illustrates model fits using the posterior predictive distributions.

It should be noted that our studies contain a relatively large number of observations per subject, and estimating hierarchical DDMs with multiple parameters (i.e. μ and x_0) as regression targets would produce prohibitive computational overhead, therefore we chose to use only μ as the regression target as it is the main parameter of interest to us.

Study 1

Table S2 shows posterior coefficient estimates for Study 1 from Eq. (S3). Regarding μ, we see that although the mean posterior estimate for frame is negative, the 94% credible interval (Highest Density Interval, HDI) for frame contains zero, therefore we cannot conclude that

[2] The HSSM package in Python, version 0.2, (Fengler et al., 2025).

framing the choice as implicit has a negative effect on μ. Table S3 shows posterior coefficient estimates for Study 1 from Eq. (S4).

Table S2: Hierarchical DDM Posterior Statistics for Study 1 (Eq. S3)

	Mean	SD	HDI 3%	HDI 97%	ESS	ESS (tail)
Intercept	0.25	0.07	0.13	0.38	472	1008
U_{diff}	0.18	0.01	0.17	0.19	23975	41297
frame implicit	-0.01	0.01	-0.02	0.01	23727	40295
x_0	0.47	0.00	0.47	0.48	21192	38546
B	2.07	0.01	2.06	2.09	16624	33464
t_0	0.24	0.01	0.23	0.25	15303	30148
RE: subj. (SD)	0.69	0.05	0.60	0.79	2044	3696

Note. Continuous predictors of drift rate ν are scaled and centered. Individual random effect (RE) estimates are omitted. ESS = effective sample size.

Table S3: Hierarchical DDM Posterior Statistics for Study 1 (Eq. S4)

	Mean	SD	HDI 3%	HDI 97%	ESS	ESS (tail)
Intercept	0.25	0.07	0.11	0.37	559	1270
frame implicit	0.00	0.01	-0.02	0.011	24521	40367
L	0.03	0.01	0.02	0.042	15752	30969
P	0.11	0.01	0.10	0.12	16305	30750
α	0.03	0.01	0.02	0.042	16431	29526
frame implicit $\times L$	-0.02	0.01	-0.03	-0.007	15586	30246
frame implicit $\times P$	-0.06	0.01	-0.07	-0.046	16355	31839
frame implicit $\times \alpha$	-0.02	0.01	-0.03	-0.006	16090	28853
x_0	0.47	0.00	0.47	0.47	21111	37497
B	2.07	0.01	2.05	2.079	17266	33471
t_0	0.24	0.01	0.23	0.24	16594	29029
RE: subj. (SD)	0.76	0.05	0.66	0.85	2077	4174

Note. Continuous predictors of drift rate ν are scaled and centered. Individual random effect (RE) estimates omitted. ESS = effective sample size.

Study 2

Tables S4 and S5 show posterior coefficient estimates for Study 2 for DDMs in Eqs. S3 and S4.

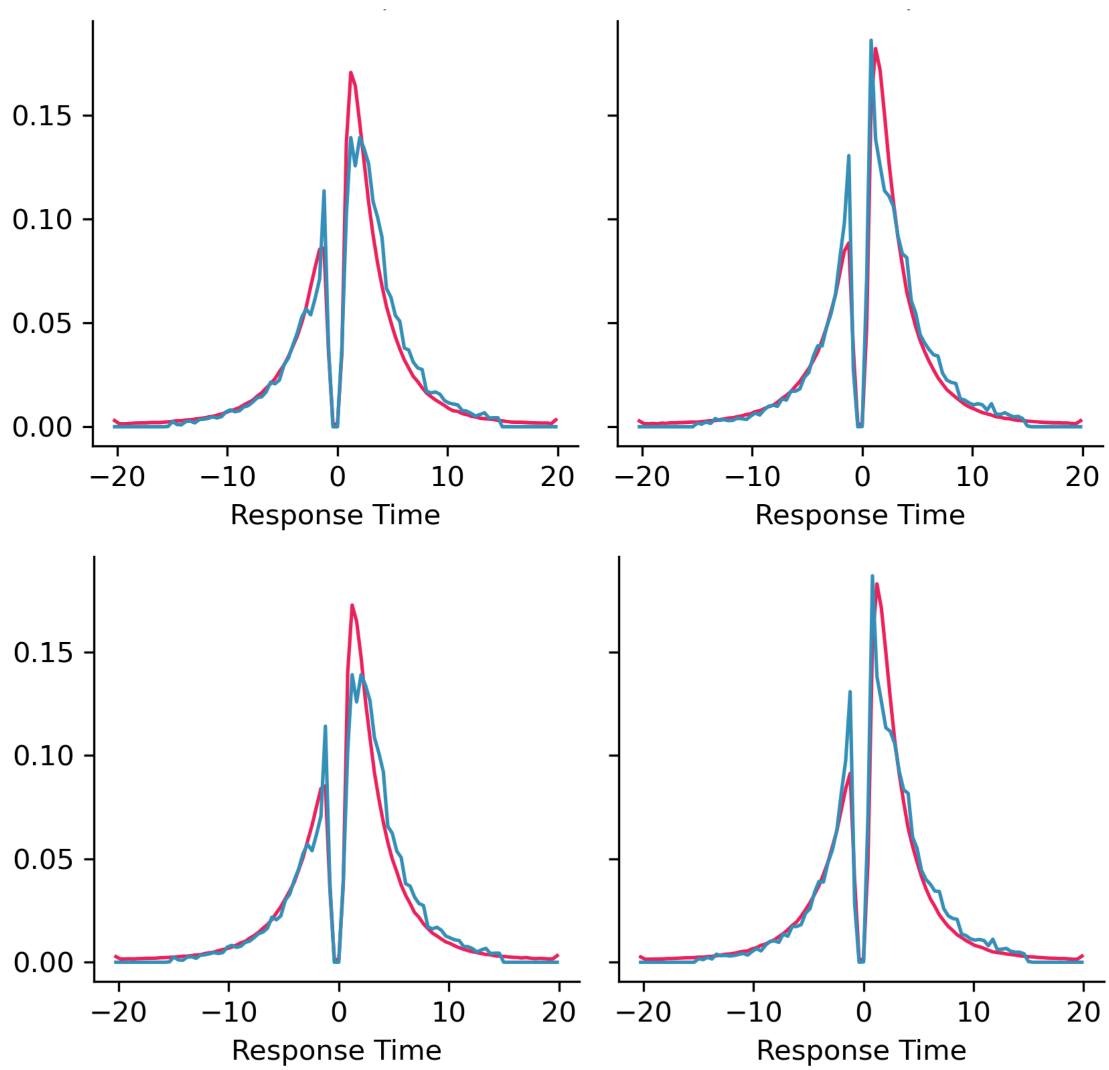

Figure S8: Posterior predictive plot for hierarchical DDM estimations in Study 1, using Eq. S3 (top) and using Eq. (S4) (bottom). Left = explicit frame, right = implicit frame. The blue lines represent observed data and the red lines represent samples from the posterior predictive distributions. Flipped values represent the response times of non-RRO choices.

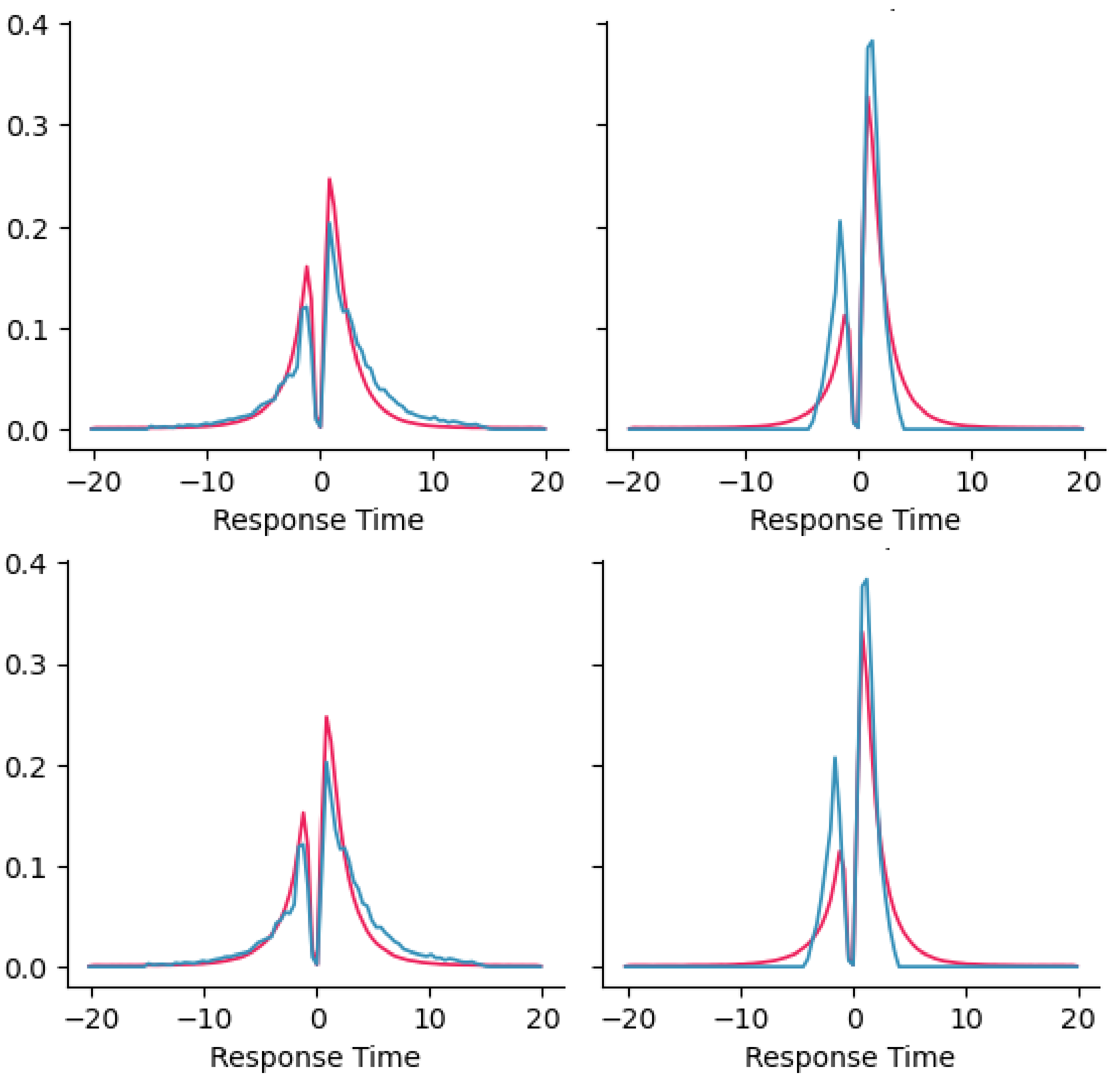

Figure S9: Posterior predictive plot for hierarchical DDM estimations in Study 2, using Eq. S3 (top) and using Eq. (S4) (bottom). Left = unrestricted frame, right = time-pressure frame. The blue lines represent observed data and the red lines represent samples from the posterior predictive distributions. Flipped values represent the response times of non-RRO choices.

Table S4: Hierarchical DDM Posterior Statistics for Study 2 (Eq. S3)

	Mean	SD	HDI 3%	HDI 97%	ESS	ESS (tail)
Intercept	0.45	0.13	0.21	0.68	380	645
U_{diff}	0.17	0.01	0.16	0.19	18313	32740
frame TP	0.32	0.01	0.31	0.34	18059	30496
x_0	0.46	0.00	0.45	0.46	16388	27019
B	1.67	0.01	1.66	1.68	15779	31585
t_0	0.25	0.00	0.24	0.25	10284	19364
RE: subj. (SD)	1.42	0.10	1.24	1.60	1757	2439

Note. Continuous predictors of drift rate ν are scaled and centered. Individual random effect (RE) estimates omitted. TP = time pressure. ESS = effective sample size.

Table S5: Hierarchical DDM Posterior Statistics for Study 2 (Eq. S4)

	Mean	SD	HDI 3%	HDI 97%	ESS	ESS (tail)
Intercept	0.44	0.13	0.206	0.68	733	1113
frame TP	0.316	0.01	0.29	0.34	15101	17813
L	0.088	0.01	0.074	0.10	11807	17309
P	0.267	0.01	0.253	0.28	11799	17099
α	-0.016	0.01	-0.029	0.00	10895	16588
frame TP $\times L$	0.046	0.01	0.03	0.062	11743	16595
frame TP $\times P$	0.144	0.01	0.13	0.161	12183	17560
frame TP $\times \alpha$	-0.044	0.01	-0.06	-0.028	11337	16946
x_0	0.458	0.00	0.453	0.46	13999	17908
B	1.692	0.01	1.682	1.70	14715	19496
t_0	0.245	0.00	0.241	0.25	10177	15697
RE: subj. (SD)	1.531	0.10	1.338	1.71	1315	1457

Note. Continuous predictors of drift rate ν are scaled and centered. Individual random effect (RE) estimates omitted. TP = time pressure. ESS = effective sample size.

Order Effect Analyses for Study 1

First Frame Only (Rounds 1-168)

Here we consider only the first frame experienced by each subject. In such comparisons, subjects are not nested within frames as framing becomes a pure between-subjects effect. Table S6 presents results from a GLMM as in Eq (1) but with simple subject random effect intercepts.

Table S6: Results From a GLMM Predicting RRO Choice in Study 1 (Rounds 4–168)

	Coef. [95% CI]
Intercept	1.17 $[0.69, 1.66]$ ***
frame implicit	-0.05 $[-0.72, 0.62]$
L	0.25 $[0.19, 0.31]$ ***
P	0.67 $[0.60, 0.73]$ ***
α	0.27 $[0.21, 0.33]$ ***
GRQ	-0.89 $[-1.35, -0.43]$ ***
CRT	0.29 $[-0.16, 0.74]$
frame implicit $\times$ L	-0.18 $[-0.26, -0.09]$ ***
frame implicit $\times$ P	-0.32 $[-0.41, -0.24]$ ***
frame implicit $\times$ α	-0.19 $[-0.28, -0.11]$ ***
frame implicit $\times$ GRQ	-0.04 $[-0.73, 0.65]$
frame implicit $\times$ CRT	0.45 $[-0.23, 1.14]$
RE: intercept (subj.)	1.66
Num. obs.	15506

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. RE = random effects. Significance levels: *** $p < .001$.

Separate Analyses for Different Orders

Here we report two different analyses. We first divide the data in two halves, in which the other one has subjects who experienced the explicit frame first, and in the other one the subjects experienced the implicit frame first. We then repeat regression analyses reported in the main text using these datasets. Table S7 presents the results from a GLMM as in Eq. (1) with simple subject random effects. Table S8 presents the results of an LMM as in Eq. (2) with simple subject random effects.

Table S7: Results from a GLMM Predicting RRO Choice in Study 1 in Two Different Orders

	Coef. [95% CI] (explicit first)	Coef. [95% CI] (implicit first)
Intercept	0.99 $[0.55, 1.42]$ ***	1.37 $[0.94, 1.81]$ ***
frame implicit	0.17 $[0.09, 0.25]$ ***	-0.09 $[-0.18, 0.00]$ *
L	0.23 $[0.18, 0.29]$ ***	0.13 $[0.07, 0.18]$ ***
P	0.61 $[0.55, 0.67]$ ***	0.49 $[0.43, 0.55]$ ***
α	0.24 $[0.19, 0.30]$ ***	0.11 $[0.05, 0.17]$ ***
GRQ	-0.82 $[-1.26, -0.38]$ ***	-0.88 $[-1.34, -0.42]$ ***
CRT	0.28 $[-0.15, 0.71]$	0.93 $[0.47, 1.38]$ ***
frame implicit $\times$ L	-0.07 $[-0.15, 0.01]$	-0.05 $[-0.13, 0.03]$
frame implicit $\times$ P	-0.30 $[-0.38, -0.21]$ ***	-0.14 $[-0.22, -0.05]$ **
frame implicit $\times$ α	-0.23 $[-0.31, -0.15]$ ***	-0.03 $[-0.12, 0.05]$
frame implicit $\times$ GRQ	-0.33 $[-0.42, -0.24]$ ***	0.03 $[-0.06, 0.12]$
frame implicit $\times$ CRT	-0.05 $[-0.13, 0.02]$	-0.25 $[-0.33, -0.16]$ ***
RE: intercept (subj.)	1.50	1.56
Num. obs.	15090	16402

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. RE = random effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

Table S8: Results from an LMM Predicting Drift Rate μ in Study 1 in Two Different Orders

	Coef. [95% CI] (explicit first)	Coef. [95% CI] (implicit first)
Intercept	0.012 $[0.004, 0.019]$ **	0.014 $[0.007, 0.022]$ ***
frame implicit	0.001 $[0.000, 0.003]$	-0.002 $[-0.004, -0.001]$ **
GRQ	-0.014 $[-0.022, -0.007]$ ***	-0.009 $[-0.017, -0.001]$ *
CRT	0.007 $[-0.001, 0.014]$	0.009 $[0.001, 0.016]$ *
RE: intercept (subj.)	0.027	0.027
RE: residual	0.045	0.048
Num. obs.	15090	16402

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. RE = random effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

Order Effect Analyses for Study 2

First Frame Only (Rounds 1-168)

Table S9 presents results from a GLMM as in Eq (1) but with simple subject random effect intercepts.

Table S9: Results From a GLMM Predicting RRO Choice in Study 2 (Rounds 4–168)

	Coef. [95% CI]
Intercept	$1.17\ [0.68, 1.66]$ ***
frame TP	$-0.45\ [-1.14, 0.24]$
L	$0.37\ [0.31, 0.43]$ ***
P	$0.57\ [0.51, 0.63]$ ***
α	$0.22\ [0.16, 0.28]$ ***
GRQ	$-0.84\ [-1.32, -0.35]$ ***
CRT	$-0.06\ [-0.58, 0.46]$
frame TP $\times$ L	$-0.26\ [-0.34, -0.18]$ ***
frame TP $\times$ P	$0.08\ [0.00, 0.16]$
frame TP $\times$ α	$-0.31\ [-0.39, -0.23]$ ***
frame TP $\times$ GRQ	$0.05\ [-0.64, 0.75]$
frame TP $\times$ CRT	$-0.24\ [-0.94, 0.45]$
RE: intercept (subj.)	1.76
Num. obs.	16630

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. TP = time pressure. RE = random effects; Significance levels: *** $p < .001$.

Separate Analyses for Different Orders

Here we report two different analyses. We first divide the data in two halves, in which the other one has subjects who experienced the unrestricted frame first, and in the other one the subjects experienced the time-pressure frame first. We then repeat regression analyses reported in the main text using these datasets. Table S10 presents the results from a GLMM as in Eq. (1) with simple subject random effect intercepts. Table S11 presents the results of an LMM as in Eq. (2) with simple subject random effects.

Table S10: Results from a GLMM Predicting RRO Choice in Study 2 in Two Different Orders

	Coef. [95% CI] (unrestr. first)	Coef. [95% CI] (TP first)
Intercept	1.30 $[0.81, 1.79]$ ***	0.79 $[0.25, 1.32]$ **
frame TP	0.34 $[0.25, 0.42]$ ***	-0.18 $[-0.26, -0.10]$ ***
L	0.37 $[0.31, 0.43]$ ***	0.12 $[0.07, 0.18]$ ***
P	0.57 $[0.51, 0.63]$ ***	0.50 $[0.44, 0.56]$ ***
α	0.22 $[0.17, 0.28]$ ***	0.06 $[0.00, 0.11]$ *
GRQ	-0.87 $[-1.37, -0.38]$ ***	-1.08 $[-1.62, -0.54]$ ***
CRT	-0.03 $[-0.52, 0.46]$	-0.11 $[-0.65, 0.43]$
frame TP $\times$ L	-0.03 $[-0.11, 0.05]$	-0.01 $[-0.09, 0.07]$
frame TP $\times$ P	0.15 $[0.06, 0.24]$ ***	0.15 $[0.07, 0.23]$ ***
frame TP $\times$ α	-0.19 $[-0.28, -0.11]$ ***	-0.15 $[-0.22, -0.07]$ ***
frame TP $\times$ GRQ	-0.08 $[-0.17, 0.00]$	0.33 $[0.25, 0.42]$ ***
frame TP $\times$ CRT	-0.26 $[-0.35, -0.18]$ ***	-0.21 $[-0.29, -0.14]$ ***
RE: intercept (subj.)	1.77	1.97
Num. obs.	16536	16964

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. TP = time pressure. RE = random effects; Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

Table S11: Results from an LMM Predicting Drift Rate μ in Study 2 in Two Different Orders

	Coef. [95% CI] (unrestr. first)	Coef. [95% CI] (TP first)
Intercept	0.018 $[0.009, 0.027]$ ***	0.007 $[-0.007, 0.022]$
frame TP	0.033 $[0.031, 0.035]$ ***	0.007 $[0.004, 0.009]$ ***
GRQ	-0.015 $[-0.024, -0.005]$ **	-0.027 $[-0.042, -0.013]$ ***
CRT	-0.006 $[-0.015, 0.003]$	-0.008 $[-0.023, 0.007]$
RE: intercept (subj.)	0.034	0.054
RE: residual	0.068	0.077
Num. obs.	16536	16964

Note. Continuous predictors are scaled and centered. Coefficients and CIs expressed in log-odds. TP = time pressure. RE = random effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

References

Fengler, A., Bera, K., Omar, A., and Frank, M. (2025). Hssm: A generalized toolbox for hierarchical bayesian estimation of computational models in cognitive neuroscience. in preparation.

Gelman, A. and Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, 7(4):457–472.

Guo, L., Trueblood, J. S., and Diederich, A. (2017). Thinking fast increases framing effects in risky decision making. *Psychological Science*, 28(4):530–543.

Ratcliff, R. and Tuerlinckx, F. (2002). Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic bulletin & review*, 9(3):438–481.