Supplementary materials
Tables

Table S1

The GLMM results for performances in the standard ITC task.

Predictor variable	Coefficient for population-level effect			Standard deviation for subject-level effect		
	M	*SD*	95% CI	*M*	*SD*	95% CI
(Intercept)	2.43	0.59	[1.29, 3.64]	0.94	0.51	[0.21, 2.16]
D_S	0.41	0.41	[−0.38, 1.25]	0.51	0.40	[0.03, 1.51]
D_L	−0.64	0.39	[−1.40, 0.14]	0.45	0.39	[0.02, 1.38]
Amount	−2.04	0.70	[−3.46, −0.68]	0.76	0.53	[0.04, 2.07]
Session	0.11	0.28	[−0.48, 0.70]	0.47	0.29	[0.14, 1.24]
$D_S \times D_L$	0.35	0.31	[−0.26, 0.94]	0.26	0.26	[0.01, 0.93]
D_S × *Amount*	0.44	0.57	[−0.68, 1.52]	0.42	0.39	[0.01, 1.42]
D_S × *Session*	−0.08	0.17	[−0.42, 0.24]	0.21	0.20	[0.01, 0.75]
D_L × *Amount*	−0.40	0.63	[−1.61, 0.86]	0.60	0.50	[0.02, 1.85]
D_L × *Session*	−0.04	0.16	[−0.36, 0.27]	0.19	0.19	[0.01, 0.70]
Amount × *Session*	−0.10	0.28	[−0.63, 0.44]	0.28	0.27	[0.01, 1.00]
$D_S \times D_L$ × *Amount*	−0.01	0.59	[−1.15, 1.13]	0.47	0.43	[0.02, 1.63]
$D_S \times D_L$ × *Session*	−0.09	0.13	[−0.34, 0.14]	0.12	0.15	[0.00, 0.52]
D_S × *Amount* × *Session*	−0.17	0.24	[−0.65, 0.29]	0.23	0.24	[0.01, 0.88]
D_L × *Amount* × *Session*	0.26	0.27	[−0.25, 0.79]	0.30	0.29	[0.01, 1.04]
$D_S \times D_L$ × *Amount* × *Session*	−0.13	0.23	[−0.57, 0.33]	0.21	0.23	[0.01, 0.80]

Note. The second to the fourth columns show estimated means, standard deviations, and 95% credible intervals for coefficients for the population-level effects. The fifth to the seventh columns show the same statistics for standard deviations for the subject-level effects. Delay to the smaller/larger reward was standardized. Each variable was coded as follows: amount combination: 3 vs. 5 = −0.5, 4 vs. 5 = 0.5; session: 1st = 0, 2nd = 1, 3rd = 2, ... GLMM: generalized linear mixed model; ITC: inter-temporal choice. D_S: delay to the smaller reward; D_L: delay to the larger reward; Amount: amount combination.

Table S2

The GLMM results for performances in the no PRD ITC task.

Predictor variable	Coefficient for population-level effect			Standard deviation for subject-level effect		
	M	*SD*	95% CI	*M*	*SD*	95% CI
(Intercept)	5.96	2.25	[1.60, 10.5]	4.07	1.38	[2.24, 7.44]
D_S	0.89	0.64	[−0.37, 2.23]	0.56	0.47	[0.02, 1.74]
D_L	0.90	0.68	[−0.55, 2.16]	0.51	0.46	[0.02, 1.69]
Session	−1.09	0.47	[−2.07, −0.18]	0.75	0.40	[0.26, 1.78]
$D_S \times D_L$	−0.19	0.65	[−1.34, 1.28]	0.55	0.46	[0.02, 1.70]
$D_S \times$ *Session*	−0.12	0.22	[−0.55, 0.28]	0.26	0.23	[0.02, 0.87]
$D_L \times$ *Session*	−0.29	0.19	[−0.64, 0.07]	0.20	0.22	[0.01, 0.77]
$D_S \times D_L \times$ *Session*	−0.05	0.16	[−0.35, 0.23]	0.13	0.15	[0.00, 0.53]

Note. The second to the fourth columns show estimated means, standard deviations, and 95% credible intervals for coefficients for the population-level effects. The fifth to the seventh columns show the same statistics for standard deviations for the subject-level effects. Delay to the smaller/larger reward was standardized. The variable session was coded as follows: 1st = 0, 2nd = 1, 3rd = 2, ... GLMM: generalized linear mixed model; ITC: inter-temporal choice. D_S: delay to the smaller reward; D_L: delay to the larger reward.

Table S3

The GLMM results for comparison of performances between the standard and no PRD ITC tasks.

Predictor variable	Coefficient for population-level effect			Standard deviation for subject-level effect		
	M	*SD*	95% CI	*M*	*SD*	95% CI
(Intercept)	4.07	1.25	[1.56, 6.67]	2.10	0.84	[0.94, 4.05]
Experiment	1.45	2.03	[−2.50, 5.65]	3.54	1.43	[1.65, 7.03]
Session	−0.58	0.39	[−1.34, 0.17]	0.63	0.39	[0.18, 1.62]
Experiment × *Session*	−0.51	0.49	[−1.50, 0.47]	0.74	0.47	[0.09, 1.88]

Note. The second to the fourth columns show estimated means, standard deviations, and 95% credible intervals for coefficients for the population-level effects. The fifth to the seventh columns show the same statistics for standard deviations for the subject-level effects. Each variable was coded as follows: experiment: standard ITC task = −0.5, no PRD ITC task = 0.5, session: 1st = 0, 2nd = 1, 3rd = 2, ... GLMM: generalized linear mixed model; ITC: inter-temporal choice.

Figures

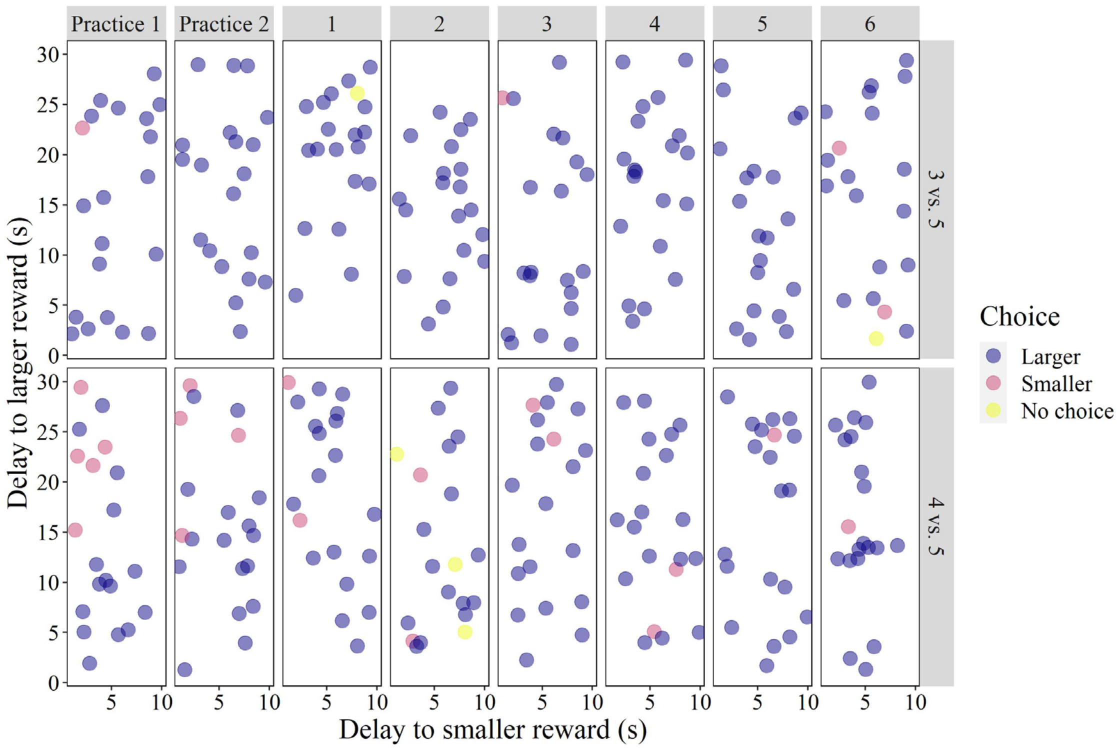

Figure S1. Hatsuka's performance in the standard inter-temporal choice task. Each panel represents a session. Upper and lower panels show data for 3 vs. 5, and 4 vs. 5 conditions, respectively.

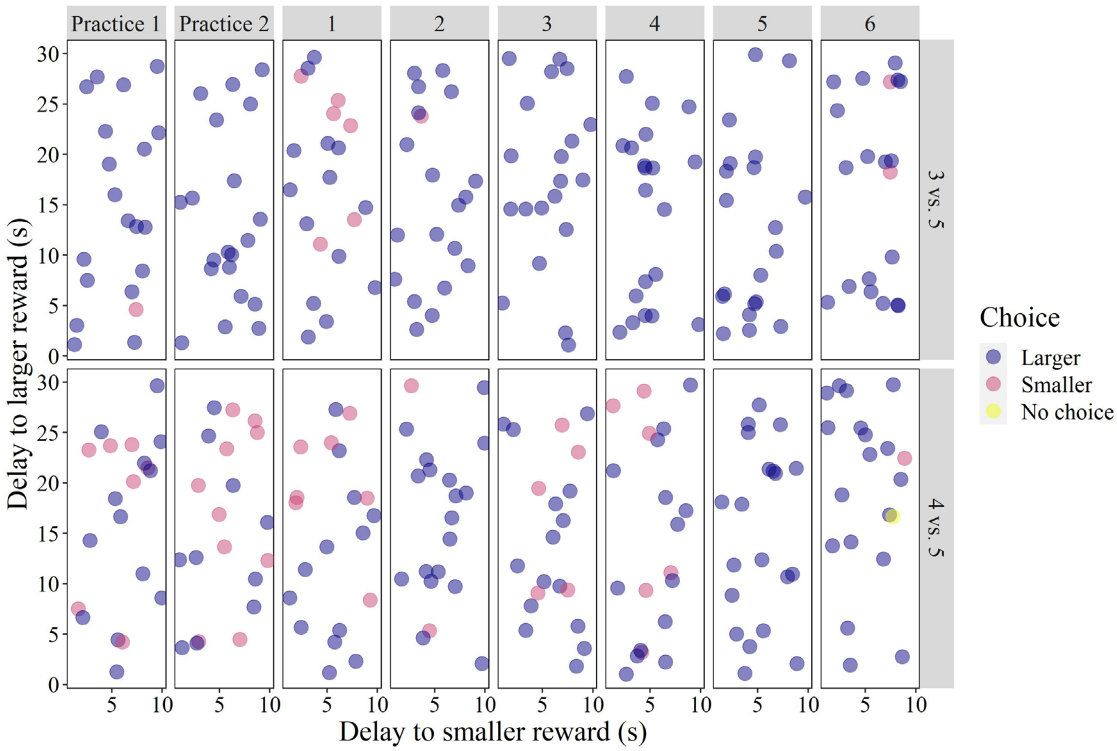

Figure S2. Iroha's performance in the standard inter-temporal choice task. Each panel represents a session. Upper and lower panels show data for 3 vs. 5, and 4 vs. 5 conditions, respectively.

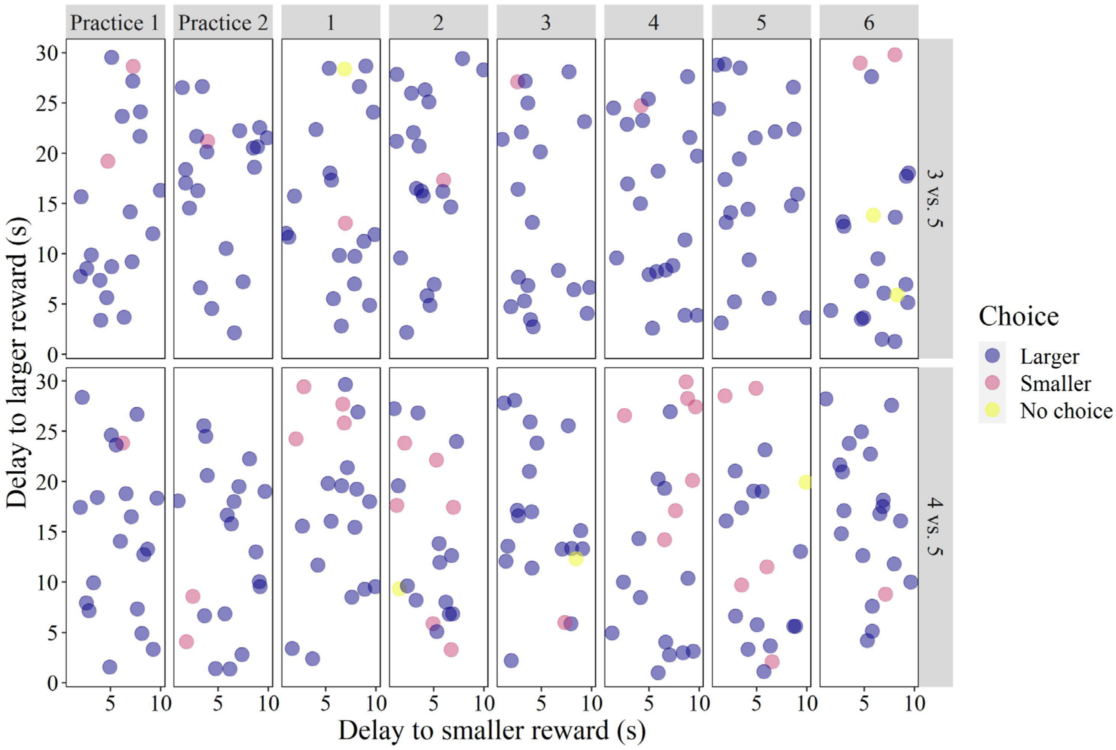

Figure S3. Mizuki's performance in the standard inter-temporal choice task. Each panel represents a session. Upper and lower panels show data for 3 vs. 5, and 4 vs. 5 conditions, respectively.

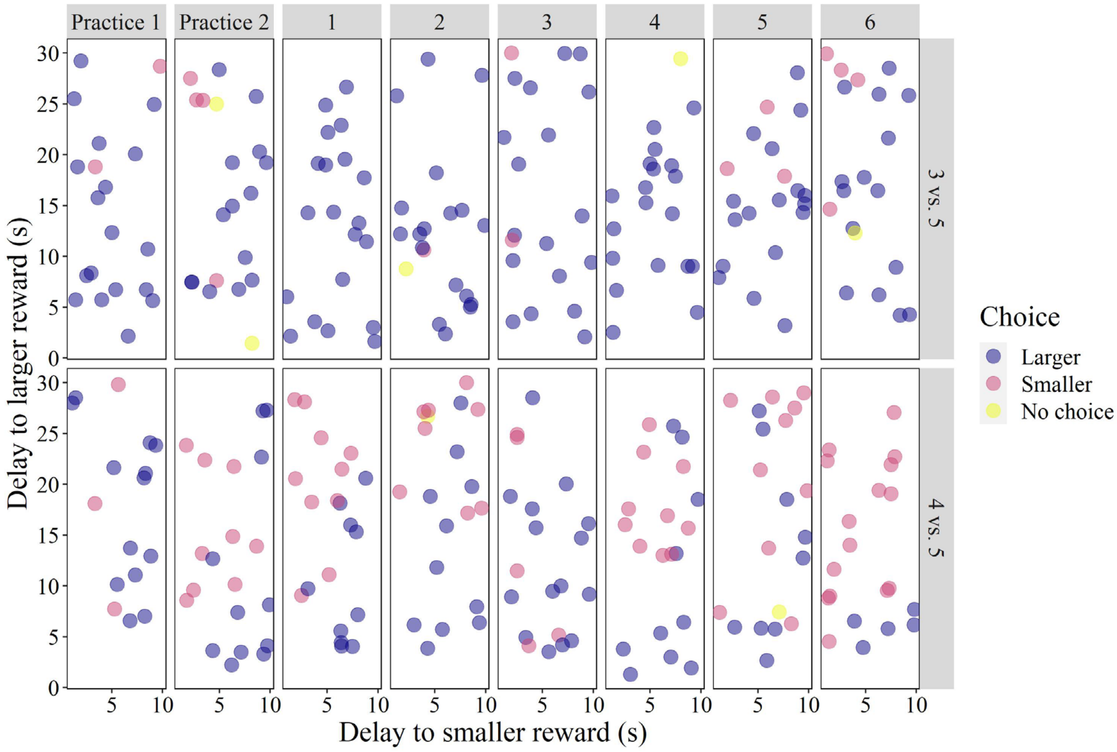

Figure S4. Natsuki's performance in the standard inter-temporal choice task. Each panel represents a session. Upper and lower panels show data for 3 vs. 5, and 4 vs. 5 conditions, respectively.

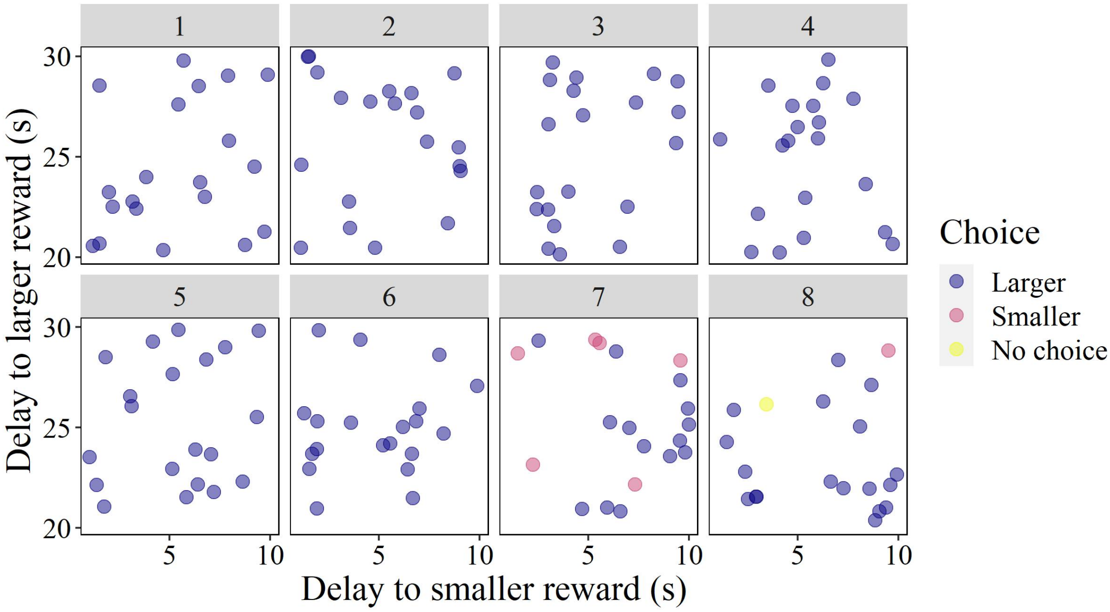

Figure S5. Hatsuka's performance in the no post-reward delay inter-temporal choice task. Each panel represents a session.

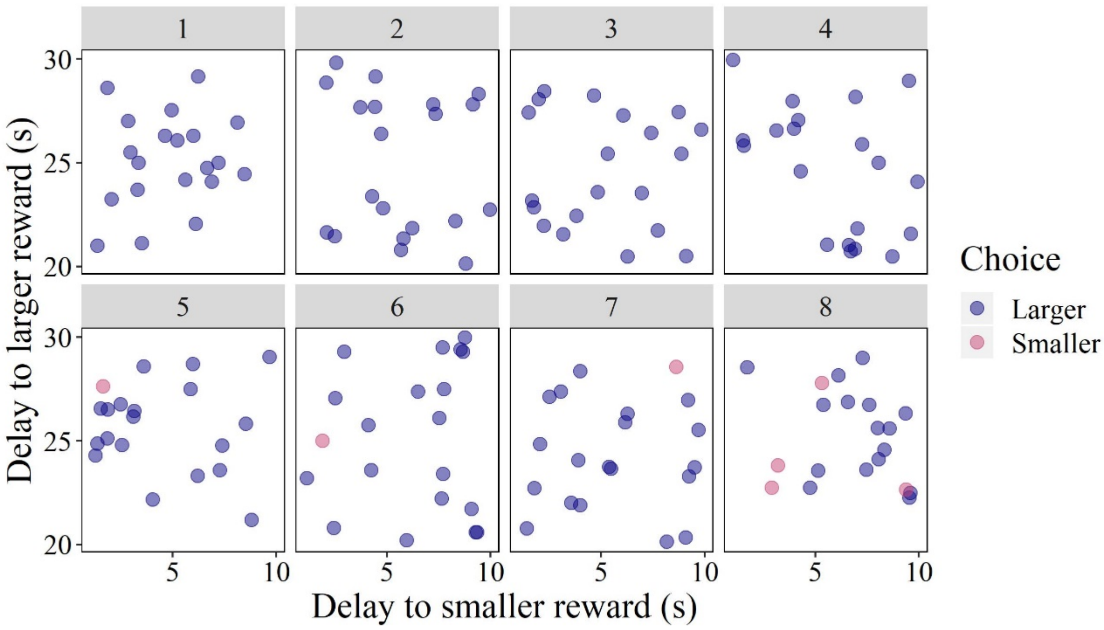

Figure S6. Iroha's performance in the no post-reward delay inter-temporal choice task. Each panel represents a session.

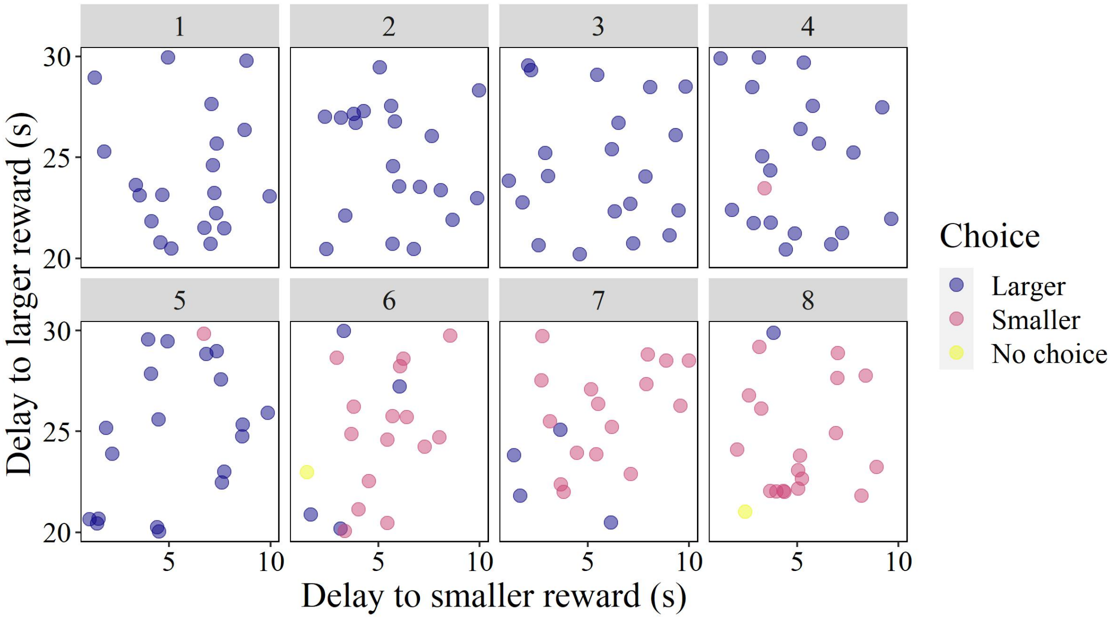

Figure S7. Mizuki's performance in the no post-reward delay inter-temporal choice task. Each panel represents a session.

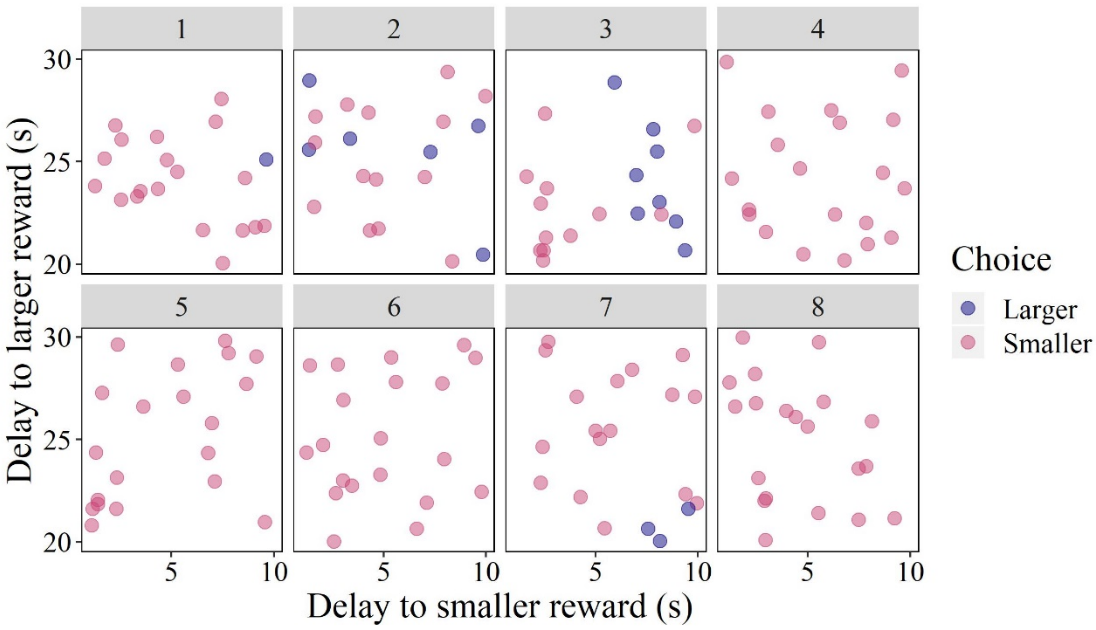

Figure S8. Natsuki's performance in the no post-reward delay inter-temporal choice task. Each panel represents a session.

Detailed methods

Determination of the reward delay for the no PRD ITC task

For the no PRD ITC task, we set the delay to the smaller reward at 1 s to 10 s and that to the larger reward at 20 s to 30 s. To maximize the long-term reward rate, a participant will choose the smaller reward when

$$\frac{R_S}{D_S + h} > \frac{R_L}{D_L + h} \tag{1}$$

where R_S/R_L is the amount of the smaller/larger reward, D_S/D_L is the delay to the smaller/larger reward, and h is the handling time. Now, the reward amount was fixed at $R_S = 3$ and $R_L = 5$, respectively. Here, the handling time refers to the time from the end of the delay to the start of the participant eating the rewards. We estimated the average handling time as approximately 5 s by direct informal observations. This was longer than the ITI (i.e., 1.5 s) and thus included instead of the ITI. By substituting these into (1), we obtained

$$3 * D_L - 5 * D_S - 10 > 0 \tag{2}$$

This holds true within the range of D_S (1 s to 10 s) and D_L (20 s to 30 s), and thus the smaller reward was optimal in terms of the long-term reward rate.

Statistical models

We used Student's t priors with degree of freedom 7, location parameter 0, and scale parameter 10 for population-level effects, and half-t priors with degree of freedom 4, location parameter 0, and scale parameter 1 for subject-level effects. Note that we did not let the brms package to estimate intercept as default, but did explicitly included the intercept term in the model formula and specified its prior. We chose those priors by referring to Stan Development Team (2019) (and also Matsuura, 2016). We ran four chains setting the iteration at 8000, of which the first 2000 were discarded as a warm-up period, and we used every fifth sample from each chain. For all parameters, the effective sample size was > 10% of the actual sample size. R hat values were 1.0 and we visually checked trace plots, which together indicate convergence across chains. A graphical posterior predictive check also indicated that the model fit the data well.

To check how the GLMM results varied depending on the prior specifications, we fitted each model (i.e., one for the standard ITC task, one for the no PRD ITC task, and the other for comparison between the two tasks) using different priors, as recommended by several researchers (e.g., Depaoli, & van de Schoot, 2017; Matsuura, 2016; van de Schoot, Winter, Ryan, Zondervan-Zwijnenburg, & Depaoli, 2017). Specifically, we fitted the same models using more fat-tailed priors by increasing the scale parameters of priors, and observed the effects on the sampling from posteriors for the population-level effects (Figure S9a). First, we changed the scale parameter of Student's t distribution for all the population-level effects from 10 to 20. In the process, we used a half-t distribution with degree of freedom 4, location 0, and scale parameter 1 for all the subject-level effects. By doing so, the overall results did not substantially change. Next, we changed the scale parameter of the half-t distribution from 1 to 5 and to 10 for all the subject-level effects. In the process, we used Student's t distribution with degree of freedom 7, location 0, and scale parameter 10 for all the population-level effects. The distribution of sampling from the posterior became wider as the scale parameter of priors for the subject-level effects increased. We visualized the means and 95% CIs of them for two of the population-level effects, which are discussed in the main text (i.e., reward amount combination in the standard ITC task: Figure S9b; session in the no PRD ITC task: Figure S9c).

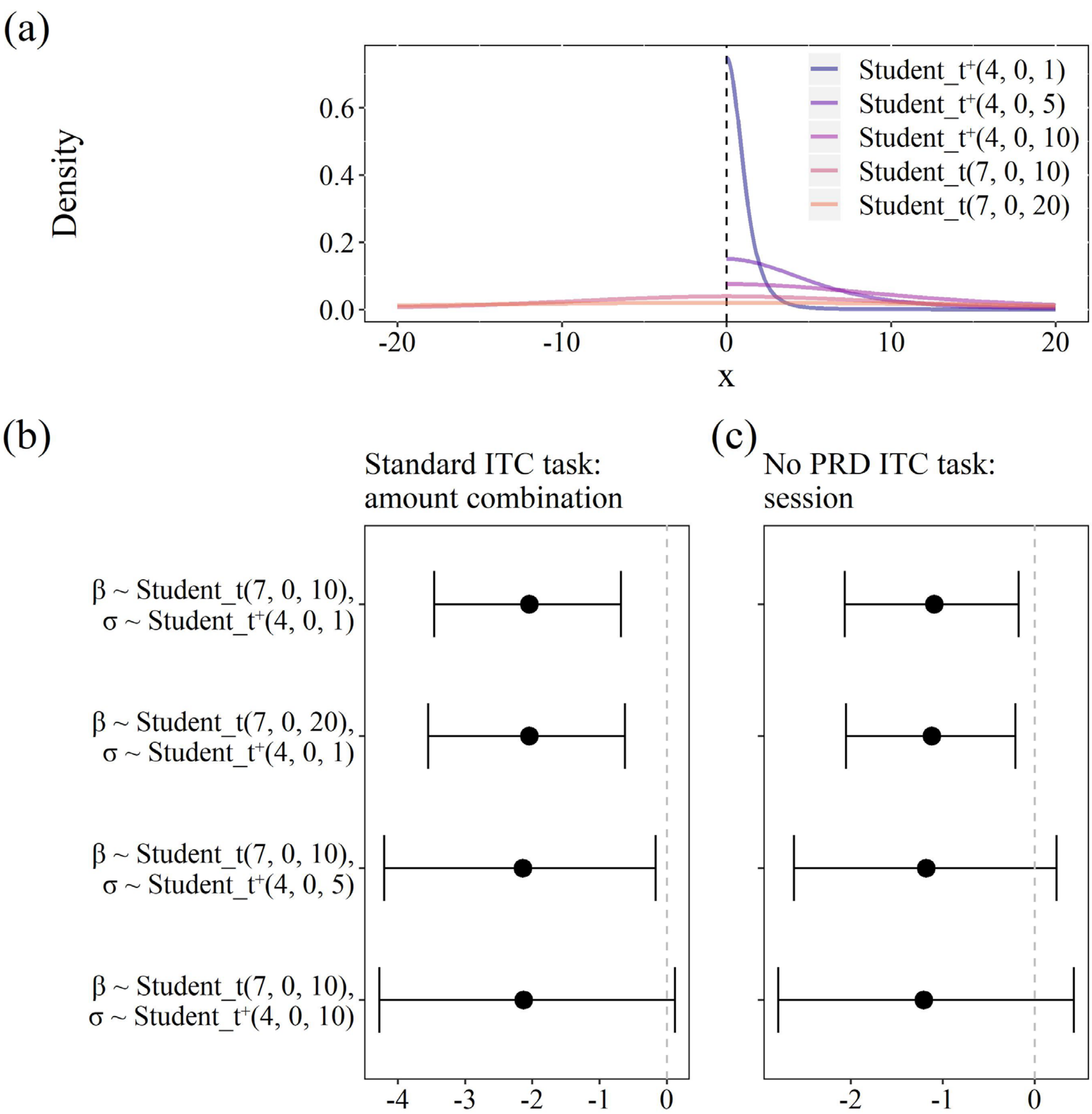

Figure S9. (a) Probability density of the priors. (b) 95% credible intervals and means of the sampling from the posterior using different combinations of priors for the amount combination in the standard ITC task and (c) for sessions in the no PRD ITC task. β and σ stand for priors of coefficients for the population-level effects and priors of standard deviations for the subject-level effects, respectively.

Supplementary references

Depaoli, S., & van de Schoot, R. (2017). Improving transparency and replication in Bayesian statistics: The WAMBS-Checklist. *Psychological Methods, 22,* 240–261. https://doi.org/10.1037/met0000065

Matsuura, K. (2016). Shuusoku shinai baai no taisyohou [Solutions for convergence problems]. In: Stan to R de beizu toukei moderingu [Bayesian Statistical Modeling Using Stan and R]. *Wonderful R* (Vol. 2, pp. 177–201). Tokyo: Kyoritsu Shuppan.

Stan Development Team (2019). Prior Choice Recommendations. Retrieved March, 2020, from https://github.com/stan-dev/stan/wiki/Prior-Choice-Recommendations

van de Schoot, R., Winter, S. D., Ryan, O., Zondervan-Zwijnenburg, M., & Depaoli, S. (2017). A systematic review of Bayesian articles in psychology: the last 25 years. *Psychological Methods, 22,* 217–239. https://doi.org/10.1037/met0000100