SUPPLEMENTARY MATERIAL

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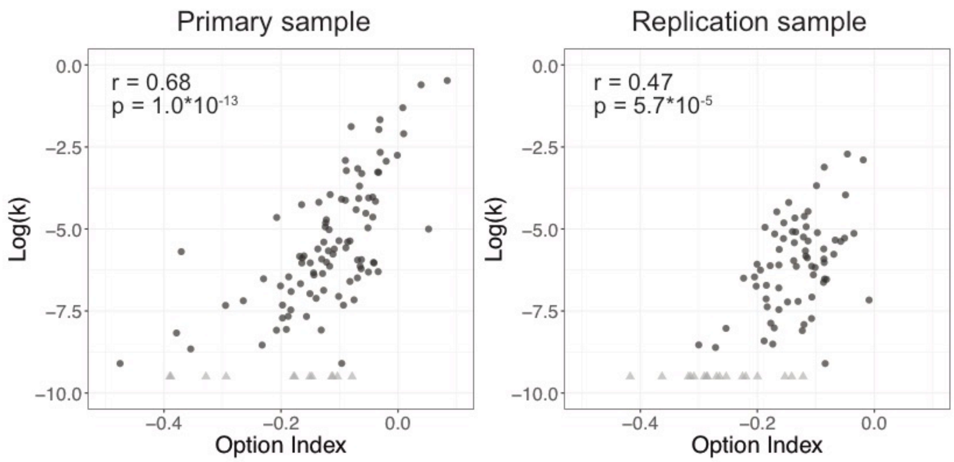
Supplementary Result 1. The Option Index correlates with discount rate

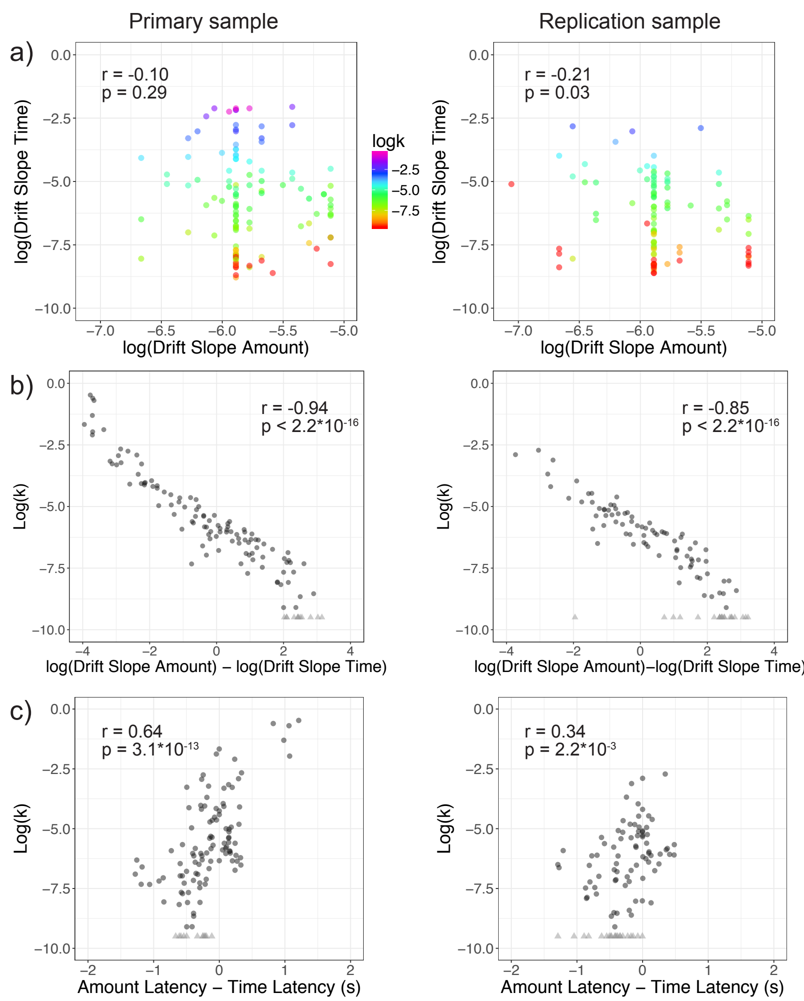
We found a positive correlation (primary: $r(91) = 0.68$, $p = 1.0 \times 10^{-13}$; replication: $r(66) = 0.47$, $p = 5.7 \times 10^{-5}$) between option index and discount rate such that more patient people had a bias to look more at the LL options, and less patient people had a bias to look more at the SS options or more evenly between the two. This validated our eye tracking by showing that participants tended to look preferentially at options they chose.



Supplementary Figure 1. Option index correlates with discount rate. Participants with insufficient eye tracking data are excluded and those with all patient choices are displayed in light gray triangles at -9.5 on the y-axis for illustration and excluded from statistics. The option index indicates whether participants looked proportionally more at the SS option (index >0) or LL option (index<0).

Supplementary Result 2. Option-wise DDM modeling: Relationship to intertemporal patience

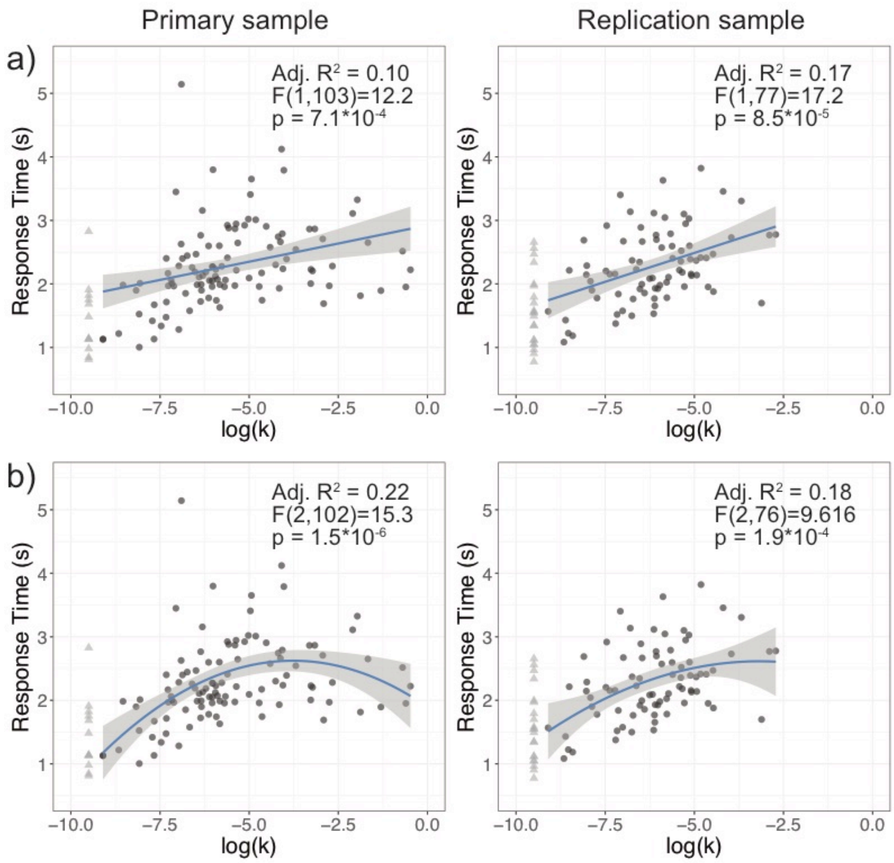
We found no correlation between amount and time drift slopes in our option-wise DDM primary sample ($r(115) = -0.10$, $p = 0.29$), however we do find a weak negative correlation in our replication sample ($r(98) = -0.21$, $p = 0.03$). Because the option-wise drift slopes were not normally distributed, we used natural-log transformed drift slopes, whereas this was not necessary in the attribute-wise model. Difference in drift slopes and discount rate are correlated in the option-wise model such that those with a higher drift slope for amount are more patient and those with a higher drift slope for time are less patient (primary: $r(103) = -0.94$, $p < 2.2\times10^{-16}$; replication: $r(77) = -0.85$, $p < 2.2\times10^{-16}$). Furthermore, we found similar results for latency such that a temporal advantage for amount relates to more patient choices and a temporal advantage for time relates to less patient choices (primary: $r(103) = 0.64$, $p = 3.1\times10^{-13}$; replication: $r(77) = 0.34$, $p = 0.0022$). Finally, as with our attribute-wise model, there is no correlation between discount rate and decision-bounds (primary: $r(103) = 0.13$, $p = 0.17$; replication: $r(77) = 0.17$, $p = 0.13$).



Supplementary Figure 2. Results from option-wise DDM modeling. (a) and (b) correspond to results presented in Figure 4; (c) corresponds to results presented in Figure 5. Participants with all patient choices are displayed in light gray at -9.5 on the y-axis for illustration and excluded from statistics.

Supplementary Result 3. Relationship between response time and discount rate

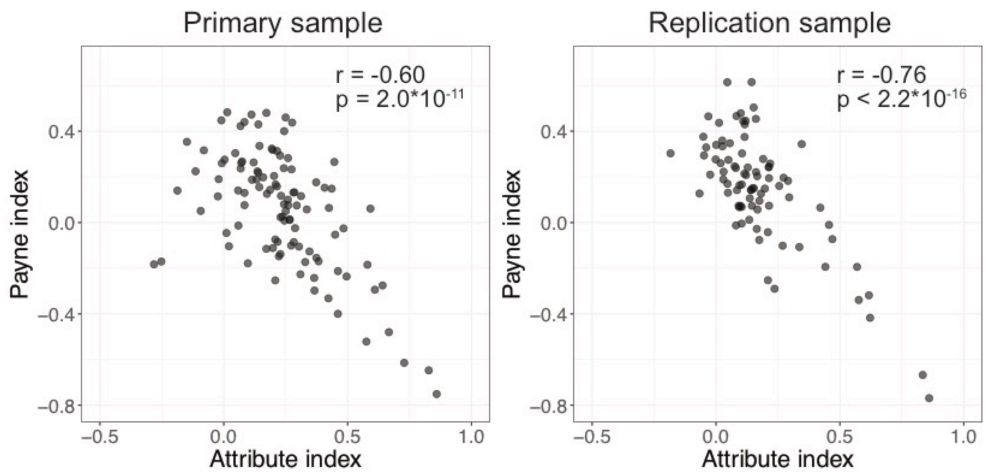
We investigated the relationship between response time and discount rate. In our primary sample, we found that a quadratic model fit better than a linear model, as it more than doubled the adjusted R-squared and the coefficient on the quadratic term is significant (b = -2.4 (SE=0.6), p = $9.0\text{x}10^{-5}$), such that both very patient and impatient people make faster choices than those in the middle. However, in our replication sample, there was a minimal change in adjusted R-squared and the coefficient on the quadratic term was not significant (b = -0.7 (SE=0.5), p = 0.18).



Supplementary Figure 3. Relationship between response time and discount rate. a) Linear models of response time on discount rate. b) Quadratic models of response time on discount rate. Participants with all patient choices are displayed in light gray at -9.5 on the x-axis for illustration and excluded from statistics, leaving final samples of N = 105 (primary) and N = 79 (replication).

Supplementary Result 4. The Payne Index correlates with the Attribute Index

The Payne Index[1] and Attribute Index are negatively correlated such that those who make more attribute-wise comparisons tend to look more at amounts, whereas those who make more option-wise comparisons tend to look more evenly between amounts and times (primary: $r(103) = -0.60$, $p = 2.0\times10^{-11}$; replication: $r(83) = -0.76$, $p < 2.2\times10^{-16}$).

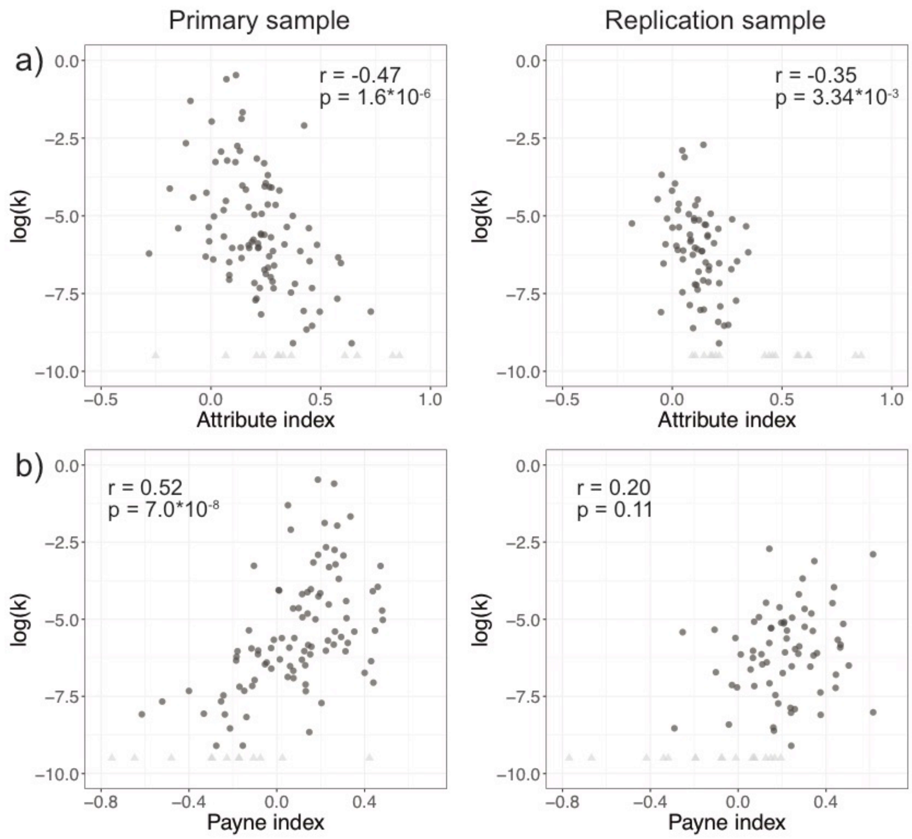


Supplementary Figure 4. The Payne Index correlates with the attribute index. Primary N=105, replication N=85. Participants with insufficient eye tracking data are excluded. The attribute index measures relative looking at amounts (index>0) versus times (index<0). The Payne index measures relative looking between options (index>0) or between attributes (index<0).

[1] Payne, J. W. Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organ. Behav. Hum. Perform.* **16,** 366–387 (1976).

Supplementary Result 5. Relationship between gaze indices and discount rate

The Attribute Index correlates negatively with discount rate, such that more patient participants look more at amounts and less patient participants look more at times (primary: $r(91) = -0.47$, $p = 1.6\times10^{-6}$; replication: $r(66) = -0.35$, $p = 0.0034$). The Payne Index is significantly correlated with discount rate in the primary sample, but this relationship is not significant in the replication sample (primary: $r(91) = 0.52$, $p = 7.0\times10^{-8}$; replication: $r(66) = 0.20$, $p = 0.11$). This may be due to many factors, including reduced variation in discount rate distribution, the change in orientation of information, or a lack of robustness of the result.



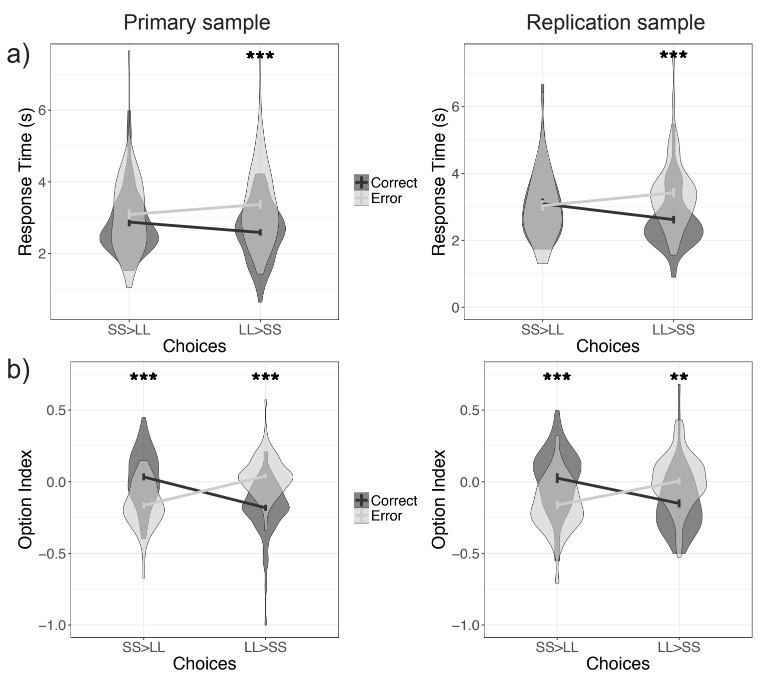
Supplementary Figure 5: Relationship between gaze indices and discount rate. Primary N=105 displayed, 93 used for analysis, replication N=85 displayed, 68 used for analysis. Participants with insufficient eye tracking data are excluded. a) The attribute index measures relative looking at amounts (index>0) versus times (index<0). b) The Payne index measures relative looking between options (index>0) or between attributes (index<0). Participants with all patient choices are displayed in light gray at -9.5 on the y-axis for illustration and excluded from statistics.

Supplementary Result 6. Error Analysis: Inter-trial differences in information processing

We examined inter-trial differences in information processing patterns, splitting trials up by choice type (LL or SS) and whether the choices were correct or errors. We determined "error" trials as choosing the option with the lower subjective value according to an individual's discount rate, *k*. We matched "correct" trials to each error trial by finding the trial closest in subjective value difference, but with the opposite choice of the higher subjective value. After excluding subjects who did not have at least three matched trials across conditions, we had the following sample sizes:

- Response Time, Primary Sample: N=58 for SS>LL, N=78 for LL>SS.
- Response Time, Replication Sample: N=40 for SS>LL, N=59 for LL>SS.
- Option Index, Primary Sample: N=58 for SS>LL, N=78 for LL>SS.
- Option Index, Replication Sample: N=39 for SS>LL, N=59 for LL>SS.

We found a significantly higher response time for errors compared to correct responses on trials in which the LL option had a higher subjective value (paired t-tests, primary: $t(77) = 7.1$, $p = 6.0 \times 10^{-10}$; replication: $t(58) = 5.3$, $p = 2.0 \times 10^{-6}$). Therefore, when people incorrectly choose a SS option over the LL option, they are slower than when correctly choosing the LL option. We also found a difference in the option index such that people tend to look more at the option they choose. Therefore, when people choose a LL option, they look more at the LL option on that trial (LL error vs. SS non-error paired t-tests: primary: $t(57) = -6.8$, $p = 7.4 \times 10^{-9}$; replication: $t(38) = -4.2$, $p = 1.6 \times 10^{-4}$) and the same pattern holds for SS options regardless of whether it is a correct or error trial (SS error vs. LL non-error paired t-tests: primary: $t(77) = 7.4$, $p = 1.6 \times 10^{-10}$; replication: $t(58) = 5.1$, $p = 4.2 \times 10^{-6}$). There were no differences in Attribute and Payne Index scores across error and correct trials.



Supplementary Figure 6. Error analysis. a) On trials where the subjective value of the LL option was greater than that of the SS option (LL>SS), response times were significantly slower on error trials (i.e., choices of the SS option) than on correct trials. b) We observed an interaction in the option index, such that both sorts of errors were associated with increased gaze time toward the subsequently chosen (and lower subjective value) option. Participants with insufficient eye tracking and all patient choices are excluded from this analysis. Violin plots show data density, and error bars represent SEM. Significance is calculated by paired t-tests. *p<.05, **p<.01, ***p<.0001.

Supplementary Result 7. Regression of option-wise DDM parameters on discount rate

A linear regression of model parameters from the option-wise DDM onto the discount rate using standardized coefficients shows similar results to the attribute-wise DDM. Difference in drift slope has the most influence, followed by latency difference with a minimal effect of bounds.

Standardized β in regression on log(*k*)		
Fit Measures	*Adj.* R^2*=0.94* *F(3,101)=502.8* $p<2.2*10^{-16}$	*Adj.* R^2*=0.92* *F(3,75)=281.4* $p<2.2*10^{-16}$
Drift Slope Difference	-0.82***	-0.90***
Latency Difference	0.24***	0.24***
Decision bounds	0.06*	0.03

Supplementary Table 1: Regression of option-wise DDM parameters on discount rate. Values from the option-wise DDM model. Standardized betas are reported with significance indicated by asterisks. $^+$p<.1, *p<.05, **p<.01, ***p<.0001.

Supplementary Result 8. Regression of DDM parameters on discount rate: Separating amount and time contributions

A linear regression of DDM model parameters revealed differences between models. In the attribute-wise model, amount and time both make separate and similarly-sized contributions. Drift slopes still have the largest impact, followed by latencies with no effect of decision bounds. However, in the option-wise model, the impact of the time drift slope is much greater than that of amount. Indeed, the impact of amount drift slope is not significant in the replication. In addition, time latency is significant in both samples, but amount latency is only significant in the primary sample. Thus, the option-wise model has a higher impact of time parameters than amount parameters, whereas the attribute-wise model has relatively even contributions of amount and time.

Measure	**Primary Sample**	**Replication Sample**
Regression of attribute-wise parameters on log(*k*)		
Fit measures	*Adj.* R^2*=0.88* *F(5,99)=151.3* $p<2.2*10^{-16}$	*Adj.* R^2*=0.88* *F(5,73)=113.7* $p<2.2*10^{-16}$
Drift Slope Amount	-0.65***	-0.59***
Drift Slope Time	0.52***	0.68***
Latency Amount	0.32***	0.25***
Latency Time	-0.22***	-0.35***
Decision bounds	-0.01	0.01
Regression of option-wise parameters on log(*k*)		
Fit measures	*Adj.* R^2*=0.95* *F(5,99)=373.9* $p<2.2*10^{-16}$	*Adj.* R^2*=0.61* *F(5,73)=26.04* $p=5.4*10^{-15}$
Drift Slope Amount	-0.08***	-0.10
Drift Slope Time	0.82***	0.69***
Latency Amount	0.25***	0.14
Latency Time	-0.13***	-0.26**
Bounds	0.02	0.21*

Supplementary Table 1: Regression of DDM parameters on discount rate. Standardized betas are reported with significance indicated by asterisks. $^+$p<.1, *p<.05, **p<.01, ***p<.0001.

Supplementary Methods 1. Analysis workflow

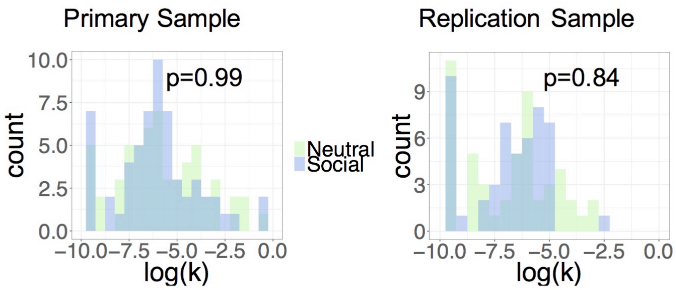
Our approach to analysis included exploratory as well as confirmatory analyses. We initially analyzed our primary sample to determine key results of interest, and then evaluated whether each of those results replicated in a second independent sample. Our first step was to fit behavior using the canonical hyperbolic model and to make sure fitted discount rates described choice by showing that subjective value drives choice and that options with similar subjective values lead to longer response times than options with very different values (Main Text Figure 1). We also examined the relationship between looking and choice to ensure that our eye gaze data were related to choice (Main Text Figure 2, Supplementary Figure 1).

Our first analysis of interest in our primary sample was look for differences across our social and neutral conditions. There were no differences in discount rate in either sample across condition, so we collapsed across this measure for all subsequent analyses. Second, we wanted to test for a relationship between survey-measured impulsivity (ABIS[2]) and intertemporal impulsivity. In our primary sample, we found the strongest relationship between the non-planning subscale and intertemporal impatience, but this did not replicate, and no subscales were significantly related to choice in our replication sample. Therefore, we did not use the ABIS for any further analyses.

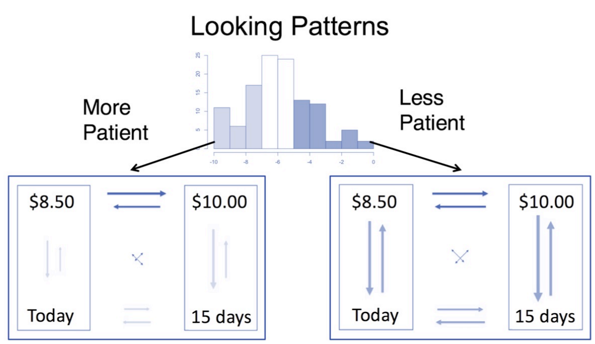
Third, we analyzed our eye tracking data in our primary sample. Because all indices measured (option index, attribute index, Payne index) showed significant relationships with the discount rate in our primary sample, we included them in our replication analyses.

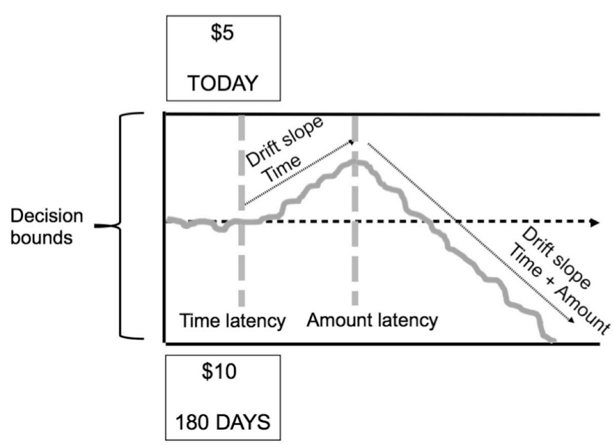
Next, we tested drift diffusion modeling as an attribute-wise model in our primary sample. Before testing in our replication sample, we drafted of our manuscript and finalized our planned analyses. In writing the manuscript, we decided to compare attribute-wise and option-wise models, as the typical form of intertemporal choice models, such as the hyperbolic model, is option-wise. Finally, when our DDM results were finalized in the primary sample, we ran the both attribute-wise and option-wise analyses in our replication sample.

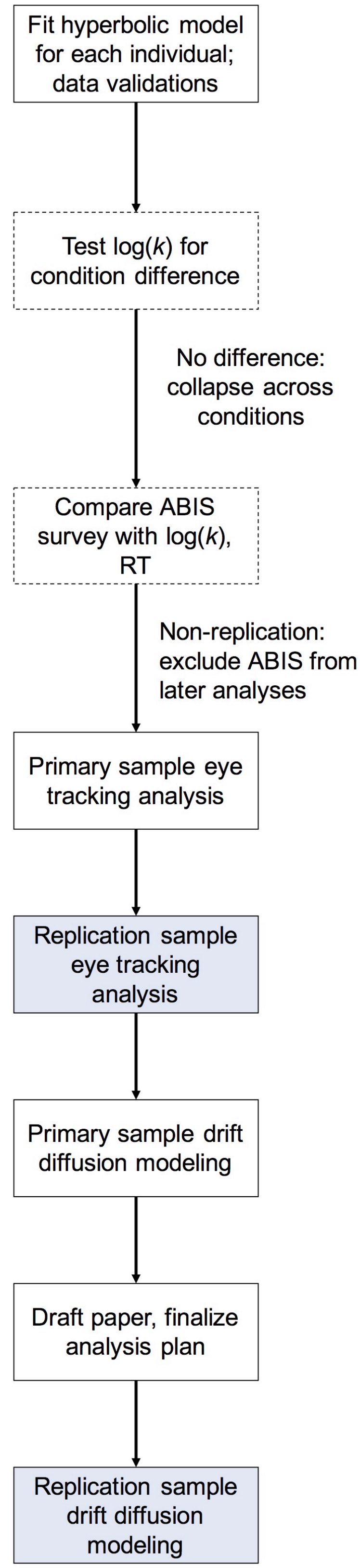
[2] Coutlee, C. G., Politzer, C. S., Hoyle, R. H. & Huettel, S. a. An abbreviated impulsiveness scale constructed through confirmatory factor analysis of the Barratt Impulsiveness Scale Version 11. *Arch. Sci. Psychol.* **2,** 1–12 (2014).



Correlations (ABIS subscales)	Primary Sample	Replication Sample
log(k), Nonplanning	r = 0.35**	r = 0.07$^{n.s.}$
log(k), Attention	r = 0.17$^{n.s.}$	r = -0.02$^{n.s.}$
log(k), Motor	r = 0.25*	r = 0.05$^{n.s.}$
RT, Motor	r = -0.06$^{n.s.}$	r = -0.11$^{n.s.}$







Supplementary Figure 7: Analysis workflow. Rectangles with dotted outlines represent analyses that were unsuccessful or did not replicate. Shaded rectangles represent replication analyses.

Supplementary Methods 2. DDM Model fitting

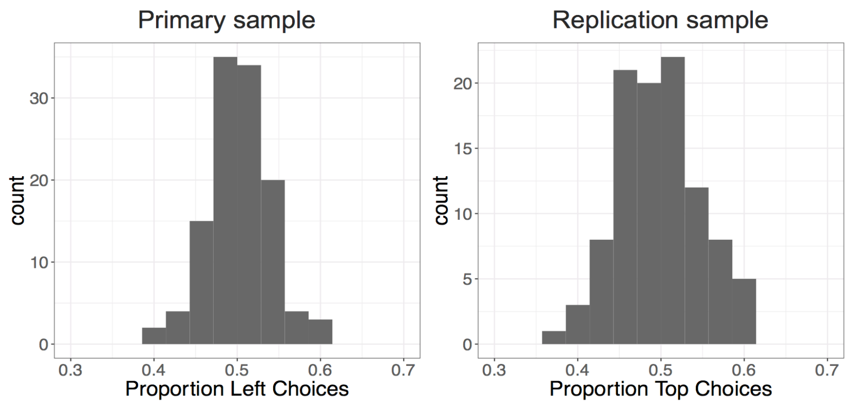
For our DDM fitting, we determined our decision bounds range by the values for which <10% of participants fit either the highest or lowest number in the range. For latencies, we used a minimum of 20 ms (our eye tracking rate is 16 ms, so we round up to 20 ms as the minimum latency to a fixation) and as maximum latency in our model fitting, we used each individual participant's average response time. For drift slopes in the attribute-wise model, we used 10 linearly spaced values from .0001 to .07, as fewer than 5% of participants in each sample required a drift slope as high as .07. For drift slopes in the option-wise model, we used 10 log-spaced values from .0001 to .1354 as fewer than 5% of participants in each sample required a drift slope as high as .1354 and the values for time drift slopes showed a normal distribution only after log-transformation (similarly to the discount rate, k).

Values used in model fitting for attribute-wise model:
Drift slope A= Drift slope T = [.0001 .0079 .0156 .0234 .0312 .0389 .0467 .0545 .0622 .0700]
Latency A = Latency T = 5 values from 20 ms to mean RT (for a given subject), linearly spaced
Bounds: [1 1.5 2 2.5 3]

For option-wise model:
Drift slope A=Drift slope T=[.0001 .0003 .0006 .0013 .0028 .0060 .0131 .0286 .0622 .1354]
Latency A=Latency T= 5 values from 20 ms to mean RT (for a given subject), linearly spaced
Bounds: [1 1.5 2 2.5 3]

<u>Supplementary Methods 3.</u> <u>Choices were not influenced by option positioning</u>

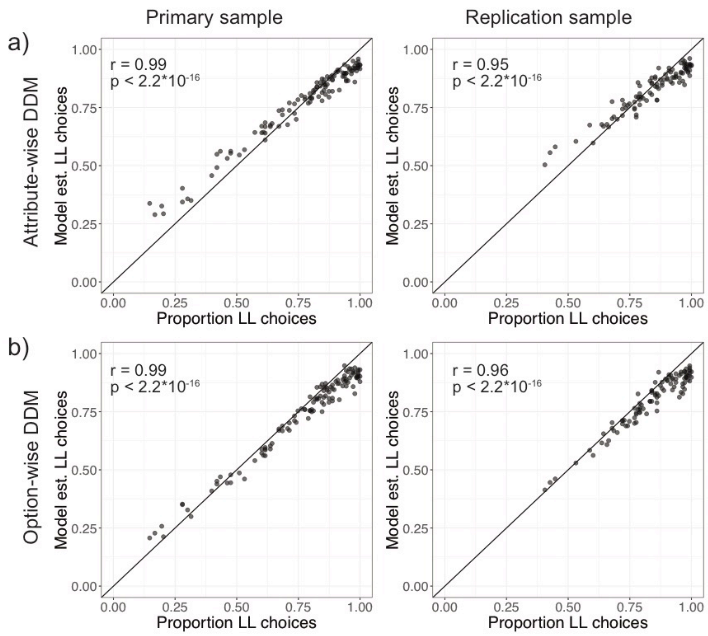
We explored the distribution of left and top choices for the primary and replication samples (on a per-subject basis). While there was variation in whether individual subjects predominantly chose left vs. right options (or top vs. bottom in the replication sample), the overall distributions were centered around 0.5. This indicates that any directional bias had minimal if any effect on our results. Given this finding – and the lack of a theoretical reason to expect that spatial bias would confound any analyses – our modeling assumed that there were no significant biases associated with spatial position.



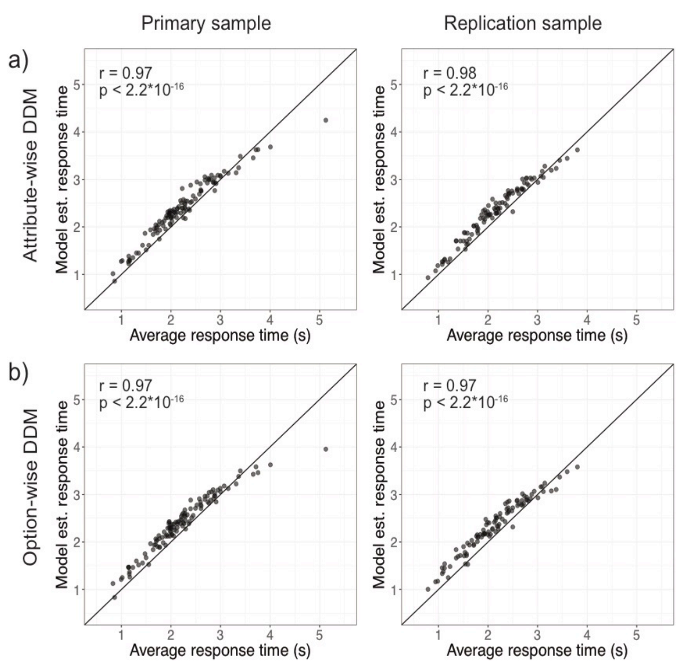
Supplementary Figure 8: Histograms of choices by direction: left/right in primary sample, top/bottom in replication sample. Primary N=117, replication N=100.

Supplementary Methods 4. Accuracy of DDM predictions: Proportion LL choices and response times

We compared the proportion of delayed (LL) choices for an individual to the model predicted proportion for the attribute-wise and option-wise models (Figure 9). We also compared the average response times and model predictions of average response times (Figure 10). Both models fit the data well.



Supplementary Figure 9: Model predictions of choice. Primary N=117, replication N=100. Line indicates equivalence between model and actual choice proportion.



Supplementary Figure 10: Model predictions of response time. Primary N=117, replication N=100. Line indicates equivalence between model and actual choice proportion.