## **Supplementary Materials**

## **Supplementary Method**

## *EEfRT Computational Modeling*

Three models, described below, were fit to each participants' data. Models included a subjective value model ("SV") that assumes that participants incorporate both trial-wise reward and probability to guide their choices, a "reward only" variant of the model that assumes that participants only attend to reward magnitude when allocating effort, thus neglecting information about probability, and a "bias model" that assumes participants do not consider reward or probability.

*SV Model*. Under the SV model, the subjective value of each option is calculated by taking the magnitude of objective reward, R, and reducing it by the amount of effort (E; .3 or 1), or cost, required to obtain the reward. The probability of receiving the reward (P; 0-1) is integrated with reward to affect subjective values by multiplying their values together (Equation 1).

$$
SV = RPh - kE.
$$
 Eq1

Critically, the subjective weighting of probability and effort on value can vary across individuals. Free parameter *h* modifies subjective value according to the probability that the reward will be received and can be interpreted as a sensitivity to probability, while free parameter *k* reduces subjective value based on the amount of effort required, independent of probability of reward receipt, and captures the degree to which rewards are discounted based on required effort.

A Softmax decision rule (Sutton & Barto, 1998) is used to transform subjective values into probabilities of selecting each option, where *t* is an inverse temperature parameter that guides choices toward options with higher subjective values:

$$
p(hard) = \frac{e^{SVhard \cdot t}}{e^{SVhard \cdot t} + e^{SVeasy \cdot t}}
$$
 Eq 2

Parameter  $t$  in the Softmax equation is an inverse temperature parameter that guides choices toward options with higher subjective values. In total, the SV model has three free parameters: k, h, and t. An additional consideration is that participants who treat probability at face value (*h*=1) may be over-penalized in model comparison for this additional free parameter. Consistent with previous work (Cooper et al., 2019) we fit an additional model variant with two free parameters (*k* and *t*) where *h* is constrained to 1. This variant was used to assess best-fitting model for each participant; participants were classified as being best-fit by the SV model if they were best fit by the full model with 3 free parameters *or* the full model with *h* constrained to 1 as the interpretation of being best-fit by either variant is that both reward and probability information were used systematically to guide choice.

*Reward only model.* The reward-only model is identical to the SV model when *h* assumes a value of zero. Under this model, reward is discounted only by the effort required to obtain it. This model only has two free parameters, *k* and *t,* and describes behavior as well as the SV model for participants who do not strongly modulate their responses based on probability but still systematically guide effort allocation on the basis of reward magnitude.

$$
SV = R - kE
$$
 Eq 3

*Bias model.* The bias model is a simple single-parameter model that assumes a consistent probability of choosing the low-effort option across trials. Free parameter *b* represents a bias

towards the low-effort option, while the probability of selecting the high-effort option is simply 1-*b*. Critically, the bias model does not include any trial-by-trial information about reward or probability. Nevertheless, this model can provide a better fit than the SV model when participants highly favor one option, respond randomly, or make choices inconsistent with the assumptions of the SV models (i.e. choosing to exert effort for low reward but not high reward).

*Model Fit.* The three models, representing three different strategies for allocating effort, were fit in Matlab using the optimization function fmincon for maximum likelihood estimation. Models were fit individually for each participant's data for each of the sessions (orientation, placebo, amphetamine 10mg, amphetamine 20mg). For subjective value models, *k* and *h*  parameters were constrained to be between 0 and 10, while *t* was constrained between 0 and 100. All models were fit with 500 random parameter initializations to avoid local minima.

*Model Comparison.* Models with a greater number of free parameters benefit from additional flexibility. To account for these differences in flexibility, we compared the fit of each model using Bayesian Information Criterion (Schwarz, 1978). BIC penalizes models that have more free parameters  $(V_i)$ , favoring more parsimonious models when log-likelihood is the same or similar. BIC was calculated based on goodness of fit (likelihood, *Li*), number of free parameters  $(V_i)$ , and the number of observations (i.e. number of trials, n):

$$
BICi = -2ln(Li) + Viln(n)
$$
 Eq 4

The BIC value of each model was calculated for each session for each individual participant and was used to classify each set of data as being best-described by the full model, reward SV model, or bias model

Additionally, BIC values were used to calculate the BIC difference measure (ΔBIC; Dai, Kerestes, Upton, Busemeyer, & Stout, 2015; Lefebvre et al., 2017) between the SV model and

the bias model, where the difference between fit of the two models provides a measure of the extent to which the SV model (i.e. the addition of trial-by-trial information) improved goodness of fit relative to the best fit obtained without trial-wise probability and reward information. Models provide a better fit than baseline models (such as the bias model) when the more complex model can capture the influence of trial-wise information on choice (Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Dai et al., 2015). The ΔBIC measure allows us to capture the fit improvement obtained by including trial-wise information:

$$
\Delta BIC = BIC_{BIAS} - BIC_{SV}
$$
 Eq 5

Participants with a positive BIC difference are better fit by the SV model, and their choices are better explained by incorporating trial-by-trial variability in reward and probability, while participants with a negative BIC difference exhibit behavior that is better explained by the simplest model.

*Simulating Changes in Effort Sensitivity.* We conducted simulation analyses to assess whether changes only to effort sensitivity parameter *k* could result in patterns of data similar to what we observed in our sample. We fit an additional variant of the full subjective value model where *k* was allowed to vary between sessions but *h* and *t* were held constant, estimating three values of *k* (0mg, 10mg, and 20mg), one value of *h*, and one value of *t* for each participant. These parameters were used to simulate 500 sets of surrogate data for each set of parameters, for each level of amphetamine. The surrogate data were averaged to provide a mean proportion of hard selections for each "participant" (set of parameters) at each reward/probability bin. Repeated-measures comparisons were used to test whether there was a significant difference at each reward/probability level.

# *EEfRT Control Analyses*

To test whether psychomotor effects of *d*-amphetamine influenced choice, we modeled key press speed on the EEfRT using a linear mixed effects model with Drug and Task Type (hard vs. easy) as fixed effects. We included Task Type as a covariate because hard tasks generally had slower key press speeds, and failing to account for this could confound effects of the drug on choice with "pure" psychomotor effects. In this case a maximal random effects model converged. We then extracted individual estimates of the linear effect of Drug from this model (there were only linear effects of Drug on both choice and keypress speed, so we did not deem it necessary to extract the quadratic effect of Drug), and entered them into the final choice model as a between-subject mean-centered covariate.

# *PRT Control Analyses*

We also tested the effect of *d*-amphetamine on discriminability, reaction time, and reinforcement schedule. We modeled discriminability using LMM with Drug and Block as fixed effects, while controlling for Session. Reaction time was modeled using LMM with Drug, Block, and Stimulus (lean vs. rich) as fixed effects, while controlling for session. We also modeled reward schedule (i.e. the number of rewarded trials) using LMM with Drug and Stimulus as fixed effects, while controlling for session.

#### **Supplementary Results**

## *Computational Modeling*

The full subjective value model was the best-fitting model for the majority of participants in all conditions (orientation, 0mg, 10mg, 20mg), indicating that the majority of participants used reward and probability information to guide choice (Table S1). Comparisons of fit and BIC difference are included in the main text.

*Association Between* Δ*BIC and Working Memory.* Previous work has shown a positive relationship between ΔBIC in the EEfRT task and cognitive functioning, where cognitive functioning as associated with increased systematic allocation of effort for rewards (Cooper et al., 2019). Consistent with this work, working memory was correlated with the degree to which participants systematically allocated effort for rewards ( $\triangle BIC$ ) during the orientation session,  $r =$ .385,  $p = .047$  (Figure S1a).

*Amphetamine Effects on Inverse Temperature.* Differences in parameters that scale subjective value in the full subjective model  $(k, h)$  are reported in the main text. We additionally examined differences in inverse temperature parameter *t* (Figure S1b)*.* While the inverse temperature parameter increased numerically under amphetamine, this effect was not significant,  $F(2, 50) = .556, p = .577.$ 

*Simulating Changes in Effort Sensitivity.* Simulated data from models varying in only parameter *k* are shown in Figure S2. Simulated data showed significant differences at every reward/probability level where significant differences were observed in the actual data (Figure S2). It should be noted that the simulated data was less noisy than the actual data and showed significant differences in additional reward/probability bins where effects did not reach significance in the actual data.

### *Manipulaton Checks*

Both the 10 and 20mg doses of *d*-amphetamine increased subjective elation immediately before the tasks at 90min; linear Drug x order4 Time interaction,  $B = 0.30$ ,  $SE = 0.13$ ,  $t = 2.35$ , p < 0.001. The 10mg and 20mg doses of *d*-amphetamine also increased reports of feeling a drug effect both before (at 90 min.) and after the tasks (at 180 min.), with 20mg continuing to elevate reports of feeling a drug effect out to the final (240 min.) time point; linear Drug x cubic Time

interaction,  $B = -8.21$ ,  $SE = 3.65$ ,  $t = -2.25$ ,  $p = 0.025$ . Finally, both the 10mg and 20mg doses of *d*-amphetamine increased mean arterial blood pressure, both before (at 90 min) and after the tasks (at 180 min and 240 min); linear Drug x quadratic Time interaction,  $B = -5.22$ ,  $SE = 1.23$ , t  $= -4.25$ ,  $p < 0.001$ . Please see Supplemental Table S2 and Figure S4.

# *EEfRT Control Analyses*

The effects of *d*-amphetamine on choice did not appear to be due to its effects on psychomotor speed. Although d-amphetamine significantly sped key pressing (linear Drug effect on speed,  $B = -0.01$ ,  $SE = 0.004$ ,  $t = -5.50$ ,  $p < 0.001$ ), the effect of drug on choice was still significant after drug effects on psychomotor speed were entered as a covariate (linear Drug effect on choice controlling for speed,  $B = 0.64$ ,  $SE = 0.28$ ,  $z = 2.24$ ,  $p = 0.03$ ).

## *PRT Control Analyses*

**Discriminability**. As expected, no significant effects of drug were found for discriminability, indicating that any effects observed are not due to changes in ability to discriminate between the stimuli. See Table S4 and Figure S5.

*Reaction Time* – RT was influenced by Drug, Block, and Stimulus. Unexpectedly, RT was slowest under 10mg of *d*-amphetamine, specifically for lean stimuli, as indicated by a quadratic effect of Drug and a linear effect of Stimulus B =  $-10.00$ , SE = 4.79, t =  $-2.09$ , p = 0.037. See Table S4 and Figure S5.

*Reinforcement Schedule* – As expected, reinforcement schedule was unaffected by the drug, suggesting that the results are not due to differing reward schedules among drug doses. See Table S4 and Figure S5.

# **Supplemental Tables**



**Table S1:** Fit Statistics. Average BIC (Bayesian Information Criterion) for each model and percentage of participants best-fit by each model in each condition.

**Table S2:** Manipulation Checks – Elation on the Profile of Mood States, Feel Drug on the Drug Effectiveness Questionnaire (DEQ), and Mean Arterial Pressure (MAP)









Intercept 20.50 Linear drug 24.32



# **Table S3**- Effort Expenditure for Reward Task Results – Hard Choice, Hard Choice by Baseline Effort, Hard Choice by Working Memory









### **Random Effects**









**Table S4.** Probabilisitc Reward Task Reults – Response Bias, Response Bias by Baseline Effort, Response Bias by Working Memory, Discriminability, Reaction Time, and Reward Scheule











Quadratic session 0.02





# **Supplemental Figures**



**Figure S1:** A) Association between working memory and ΔBIC during the orientation session.

B) Inverse temperature parameter (log transformed) across placebo and amphetamine conditions.

**Figure S2**. Proportion of hard effort selections for simulated data (top) and actual data (bottom).

Error bars represent standard error of the mean.  $* p < .05 ** p < .01 ** p < .005$ 





**Figure S3:** Manipulation Checks A) Elation B) Feel Drug C) Mean Arterial Pressure

**Figure S4:** Probabilistic Reward Task A) Response Bias B) Discriminability C) Reaction Time D) Reinforcement Schedule



## **Supplementary References**

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