Effortful goal-directed behavior in schizophrenia: computational subtypes and associations with cognition

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Supplementary Materials

Supplementary Method

Inclusion and Exclusion Criteria

For Sample 1, inclusion criteria for participants with schizophrenia was based on the Structured Clinical Interview for the DSM-IV-TR, as described in (Barch, Treadway, & Schoen, 2014). Patients had to meet criteria for schizophrenia or schizoaffective disorder, and were excluded for major depressive episode or dysthymia within the last year, mental retardation, head injury with loss of consciousness or neurological sequelae, or substance abuse or dependence within the last six months. Healthy controls were excluded for family or personal history of psychosis or bipolar disorder. For Sample 2, inclusion criteria for people with schizophrenia required a diagnosis of schizophrenia as determined by the SCID for DMS-IV and age of 18-60, as described in Reddy et al., 2015. Patients were also excluded for mental retardation, clinically significant neurological disease or history of serious head injury, substance abuse in the past month or substance dependence within the last six months. In addition, participants in Sample 2 were required to be clinically stable, assessed as experiencing no inpatient hospitalizations within the prior 3 months and no changes in antipsychotic medication type within the last 4 weeks. For healthy controls, inclusion criteria again required absence of schizophrenia spectrum disorder or other psychotic or recurrent mood disorder and no family history of a psychotic disorder. Three participants from Sample 1 were excluded for response rates 2.5 standard deviations below the mean (Mean = 44 trials, SD = 9.24; Excluded participants responded on 2, 3, and 15 trials).

Measures used in each sample

Positive symptom for Sample 1 were assessed with the Scale for the Assessment of Positive Symptoms (Andreasen, 1984) and negative symptoms assessed with the Scale for the Assessment of Negative Symptoms (Andreasen, 1989). Symptoms for Sample 2 were assessed with the Positive and Negative Syndrome Scale (Kay, Fiszbein, & Opfer, 1987) and the Clinical Assessment Interview for Negative Symptoms (Kring, Gur, Blanchard, Horan, & Reise, 2013). Cognition was assessed in Sample 1 using Wechsler Adult Intelligence Scale Matrix Reasoning (Wechsler, 2014), while the MATRICS Consensus Cognitive Battery (MCCB) was utilized in Sample 2 (M. F. Green & Nuechterlein, 2004). The MCCB is comprised of 10 tests designed to assess seven domains of cognition, including: processing speed, attention/vigilance, working memory, verbal memory, visual memory, reasoning and problem solving, and social cognition. As reported previously (Reddy et al., 2015), T-scores in these seven domains were computed for each subject, with correction for age and gender.

Subjective Value Model – Expanded Description

Computational models of subjective value use mathematical equations to combine multiple sources of information (e.g. reward, probability, delay) into a single subjective value for each presented option. This type of model has long been used to evaluate preferences for different options, including preferences for immediate or delayed rewards and rewards of varying probability (see Frederick, Loewenstein, & O'donoghue, 2002; L. Green & Myerson, 2004). Recently, this type of modeling approach has been applied to EBDM (Hartmann, Hager, Tobler, & Kaiser, 2013; Klein-Flugge, Kennerley, Saraiva, Penny, & Bestmann, 2015; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010). In these models, the subjective value of an option is calculated by taking the magnitude of objective reward, R, and reducing it by the amount of effort, or cost, required to obtain the reward.

$$SV = R - E \qquad \text{Eq 1}$$

The subjective preferences of individuals are captured by allowing the individual components to be weighed with free parameters that are fit independently to each participant's data. In the case of effort discounting, this is often captured by adding free parameter, *k* (Equation 2).

$$SV = R - kE \quad \text{Eq 2}$$

The choices of an individual who perceives the required effort to be extremely costly or undesirable would be best described a higher value of *k* that results in lower subjective values for high-effort options. In this example, the effort discounting function follows a linear function. Multiple studies suggest that effort discounting may instead follow convex functions (Hartmann et al., 2013; Klein-Flugge et al., 2015). While the design of this study only has two levels of effort, we have found that more complex functions provide a better fit in samples with multiple levels of effort (Arulpragasam, Cooper, Nuutinen, & Treadway, 2018).

The EEfRT differs from the effort discounting tasks to which these models have previously been applied in one key way—the addition of probability information on each trial. The inclusion of variable probability was added to provide greater similarity to real-life decisions, where effort must often be exerted for rewards that are uncertain. Reward and probability are integrated together affect subjective values by multiplying their values together (Equation 3). For example, a value of $2 with only 50% probability may have a subjective value of $1.

$$SV = R*P \quad \text{Eq 3}$$

As with effort discounting, the effect of probability on subjective value can vary across individuals. Here, we add a free parameter, *h*, that allows for this variation (Eq 4). An individual with an aversion to uncertain probabilities would be fit with a higher *h* parameter. In the example above ($2 for 50% probability), an *h* of 2 would reduce the subjective value to $0.50, while the same reward ($2) for 88% probability would be $1.54.

$$SV = R*P^h \quad \text{Eq 4}$$

For this analysis, we combine effort discounting from Equation 2 and probability discounting from Equation 4 to calculate subjective values based on the combination of reward, effort, and probability.

$$SV = R*P^h - kE \quad \text{Eq 5}$$

Subjective values are transformed into probabilities of selecting each option using the Softmax decision rule (Sutton & Barto, 1998), where *t* is an inverse temperature parameter that reflects a tendency to favor options with higher subjective values:

$$p(\text{hard}) = \frac{e^{SV\text{hard}\cdot t}}{e^{SV\text{hard}\cdot t} + e^{SV\text{easy}\cdot t}} \quad \text{Eq 6}$$

Thus, the Subjective Value model that we fit to our data has three free parameters: *k*, *h*, and *t*. The *k* parameter reduces subjective value based on the amount of effort required, the *h* parameter modifies subjective value according to the probability that the reward will be received, and the *t* parameter guides choices toward options with higher subjective values.

Additional Model Variants

Here, we consider additional variants of the subjective value model that were not included in the main analyses.

Probability Only

The "probability only" model estimates subjective values based only on the probability of receiving a reward. In this model, the subjective value of choosing low effort is constant (SV = 1), and the subjective value of the high effort option is represented by Equation 7, where P is probability and *a* is a free parameter.

$$SV = P^{*}a \quad \text{Eq 7}$$

The value of the reward itself is not included in the estimation of subjective value. Thus, this model assumes that participants do not modulate their choices based on reward, but attend to the probability of receipt to guide their decision whether or not to expend effort.

Fatigue

We next tested a variant of the subjective value model with an additional free parameter representing potential fatigue. In this model, the value of *k* was allowed to increase or decrease as the experiment progressed. Here, the subjective value was represented by Equation 8,

$$SV = R^{*}P^{h} - k^{\circ}{}^{*}E \quad \text{Eq 8}$$

Where k° is initialized to free parameter *k* and is modified on each trial according to Equation 9.

$$k^{\circ} = k^{\circ} * y \quad \text{Eq 9}$$

Under this model, effort discounting could increase or decrease on each trial according to the value of free parameter *y*, which was constrained to have a value between 0 and 2.

Assessing Model Fit

In addition to BIC, the fit of each model can be described using "pseudo-r^2" metric (Camerer & Hua Ho, 1999; Daw, 2011). Pseudo -r^2 is a statistic that compares the log-likelihood under the candidate model (M) to the log likelihood under chance (C). Pseudo-r^2 was calculated for each model for each participant and averaged across participants to obtain the Pseudo-r^2 for each model.

$$\text{Pseudo-}r^2 = 1 - (C/M) \quad \text{Eq 10}$$

We additionally examined the exponentiated likelihood per trial (Li/n) of the full subjective value model to verify that the per-trial likelihood was better than chance, and calculated the percentage of choices for each participant that could be accurately captured by the model. We used the best-fitting parameters for each subject, as determined by minimized negative log-likelihood, to calculate the subjective value of each option and the probability of selecting each option on each trial. If the model estimated greater than 50% probability of selecting the option that the participant actually selected, the trial was counted as correctly predicted, otherwise the trial was counted as incorrectly predicted.

Simulation and Recovery Analyses

Parameter Recovery To further validate model fit for these samples, we conducted simulation analyses to verify that the best-fitting parameters were precise enough to be recovered from simulated data. For this analysis, we first created surrogate EEfRT data from each participants' best-fitting parameters. Each set of simulated data was 50 trials long and was generated using the trial-wise reward values and probabilities available in the actual task. On each trial, the parameters were used to generate subjective values of each option and the probability of choosing the hard task using the Softmax decision rule. The choices were assigned probabilistically on each trial. For example, if the model-determined probability of selecting the hard task on a

given trial was .9, the choice would be assigned as hard with a probability of .9, and assigned as easy with a probability of .1. Thus, repeating this procedure multiple times results in sets of data with slight variation. This procedure was repeated 50 times for each set of parameters, resulting in 50 data sets for each parameter set. Each of these data sets was then fit with the subjective value model described above.

Model Recovery Surrogate data was generated under each model (full SV, reward only, bias) using the procedure outlined above and each candidate model was fit to this surrogate data using the model comparison procedure described in the main text to determine whether our procedure could correctly identify the data generated by each model. We first utilized the parameter values that provided the best-fit for each model for each participant. For each set of parameter values, 50 sets of surrogate data were created.

We next generated surrogate data over a range of parameter values for the full subjective value model to examine the ability of our model comparison procedure to correctly identify the model used for generation at different parameter values. For this simulation, the value of the inverse temperature parameter was held constant at 30. The value of k ranged from 0 to 5 in increments of 0.5, and the value of h ranged from 0 to 10 in increments of 0.5.

Medication Effects

We additionally examined whether or not our model-based groupings differed in medication status. We first examined the frequencies of participants taking typical and atypical medications in each group (bias, reward, and full SV). For this analysis, participants were each categorized as taking typical, atypical, both, none, or unknown. Previous work has shown that patients on first generation drugs are less responsive to increasing reward levels (Gold, Waltz, & Frank, 2015). Gold et al. (2015) additionally distinguished between two atypical medications with different D2 affinities, examining differences in willingness to work for rewards in patients taking clozapine monotherapy (low D2 affinity) and risperidone monotherapy (higher D2 affinity), finding that the clozapine group showed sensitivity to cost/benefit tradeoffs (selecting higher effort as rewards increased) while the risperidone group chose high effort at higher rates but with less sensitivity to reward. If this

pattern were reflected in model fit, we would expect that participants taking clozapine monotherapy may be more often fit by the SV models, while participants taking risperidone may be more often fit by the bias model. To test this, we examined the proportion of subjects best-fit by each model in participants taking clozapine monotherapy (n=11) and risperidone monotherapy (n=21).

EBDM Within Model-Defined Sub-Groups

Having identified sub-groups of both individuals with schizophrenia and healthy controls who were best fit by the full-SV, reward, and bias models, respectively, we performed analyses comparing patients and controls within model-defined sub-groups. Individual participants best-fit by the same model can show substantial variability in behavior. For example, the proportion of high-effort options selected by participants best-fit by the bias model still ranges from 0 to 100% of trials. Consequently, an important question to ask is whether the commonly observed reduction in willingness to exert effort in patients with schizophrenia relative to healthy controls, particularly at higher levels of reward, persists even within these subgroups. For this analysis, we conducted repeated-measures ANOVAs for each model-derived subgroup (full-SV, reward only, and bias) on the proportion of high-effort choices with two levels of probability and four levels of reward as within-subjects factors, and patient group as a between-subjects factor.

Supplementary Results

Model Fit

The average BIC values, average best-fitting parameter values, and pseudo-r^2 values for each of the models are included in Table S1. The distribution of fit values (BIC) for participants with schizophrenia and healthy controls are displayed in Figure S1. Comparisons in demographics, symptoms, and cognitive functioning between patients in these model fit groups are reported in the main text and included in Table S2. The main text also includes stepwise regressions predicting model statistics (change in BIC, k) from demographics, symptoms, and cognitive functioning that are summarized in Table S3.

Across all participants, the average likelihood per trial under the Subjective Value model was 0.72 ($M_{patient}$ = .72, $M_{control}$ = .73), significantly higher than chance levels of .5, $t(254) = 22.960$, $p < .001$. Overall, the proportion of choices correctly predicted by the SV model was .833 (SD = .125). The means for participants with schizophrenia and healthy controls were .828 (SD = .132) and .840 (SD = .115), respectively, and were not significantly different, $t(253) = .728$, p=.432.

While we used BIC-based model groupings in the main text to compare the frequencies of model fit across individuals with schizophrenia and controls, results were very similar using AIC (Akaike's Information Criterion; (Akaike, 1974). Model classification using AIC overlapped with BIC-based classification on 92% of participants. When classifying based on Akaike's Information Criterion instead of BIC, X2 (2, N=255)=9.851, p=.007 (For controls, full-SV=.51, reward-only =.25, bias=.24; for schizophrenia, full-SV=.35, reward-only =.23, bias=.42). Significant differences in the frequency of model fit (Chi-square) across controls and individuals with schizophrenia was also consistent when only using the bias model and the full-SV model with BIC, X2 (1, N=255)=8.006, p=.005 (SV control=.60, SV schizophrenia=.42), and AIC, X2 (1, N=255)=8.757, p=.003, (SV control=.70, SV schizophrenia=.52).

Additional Model Variants

The average BIC for the "probability only" model was 51.42 (higher than the bias model average of 50.78) and only provided a better fit than the other model variants for 7% of participants. The average BIC of the SV model with an additional parameter representing fatigue was 45.96 (Full SV model average BIC= 44.96), and only improved fit for 11% of participants. While these models may provide better fit in other sets of data, they were not included in the final analysis for this sample due to their relatively poor fit.

Simulation and Recovery

Parameter Recovery

Here, we compare the original parameters used to generate the data to the mean of each parameter value obtained from fitting the SV model to our simulated data. Each of the three parameters and the fit estimate were

strongly correlated with the simulated values (ps < .001, correlation coefficients in Table S4). These associations were consistent within each sample, and within people with schizophrenia and healthy controls.

Model recovery

The results of the model recovery analyses are report in Table S5-S8 as the proportion of surrogate datasets recovered by each candidate model. If model recovery is good—indicating good reliability of our models—the model used to simulate the data will be identified as the best-fitting model at high rates. If the models that generate the data cannot be identified (i.e. other models are recovered as best-fitting at similar or better rates), we lose confidence in our model comparison procedure to accurately categorize subjects. While we typically expect the model used to generate the surrogate data to be recovered at high rates, there are some exceptions where we would expect an alternate model to provide a better fit. Specifically, we expect that data generated from a more complex model (i.e. full SV model) will be recovered by a simpler model (i.e. reward only or bias model) under conditions were the parameter values used to simulate the data represent behavior that is captured by the simpler model. For example:

- When the *h* parameter is zero in the full SV model. With an *h* of zero, rewards are not discounted by probability. Using reward information while failing to utilize probability information is the definition of the reward only SV model—the reward only model is in fact the nested case of the full SV model where $h = 0$. Thus, data simulated from the full SV model under this condition ($h = 0$ or close to 0) should be recovered by the reward only model, which has one fewer free parameter and is penalized less than the full model.
- With more extreme parameter values the SV models can produce behavior that entirely favors high effort (choose all hard) or entirely favors low effort (choose all easy). Choosing all hard or all easy indicates that choices are not modulated by reward or probability, consistent with the interpretation of the bias model. Thus, under more extreme parameter values, we expect that data simulated from the SV models will be recovered by the bias model.

To illustrate the dependence on parameter values, model recovery at different parameter values is presented in Table S5-S7. Surrogate data from the full SV model at different parameter combinations are classified as being best-fit by the full SV model (Table S6), reward only model (Table S7), or bias model (Table S8) and interpreted below.

Table S5 shows the proportion of datasets simulated by the full SV model that are recovered by the full SV model. At moderate values of *k* and *h*, recovery of the full SV model is very good. At higher values of *k* and *h* (bottom right quadrant), subjective values are discounted toward zero and data begins to be recovered by the bias model. This is as would be expected. Generating data from the SV model with a very high *k* parameter (high effort discounting) produces surrogate data with all (or almost all) low-effort selections. As the model comparison procedure favors the most parsimonious (simplest) model, data produced by the SV model that can also be well described by the bias model (i.e. choosing all one option) is recovered by the simplest model.

Table S6 shows the proportion of datasets simulated by the full SV model that are recovered by the reward-only model. Critically, when the *h* parameter is 0, data simulated from the full SV model is often best fit by the reward-only model, as we would expect. When the *h* parameter is not 0, the reward only model very rarely provides the best fit for data simulated from the full SV model.

Table S7 shows the proportion of datasets simulated using the full SV model that are recovered by the bias model. At high values of *k* and *h*, the bias model is often the best-fitting model. Likewise, data generated from the full SV model with a *k* and *h* parameters of zero (no discounting) highly favors the higher effort/high reward option (i.e. choose all hard), and is recovered as high rates by the bias model. Importantly, the interpretation of the data in the cells is consistent with the bias model: individual choices on each trial were not guided by variations in reward amount or probability. When data is simulated at moderate values of *h* and *k*, the bias model rarely provides the best fit.

We additionally tested the ability of our model comparison procedure to reliability capture the model that simulated the data when the parameter values are those of our real participants. Due to the dependence on parameter values illustrated above and in tables S5-S7, we would expect model recovery to be high for the SV models when data is simulated from parameters of the participants who were best-fit by each of the SV models, and lower when simulated from the parameters of participants best-fit by the bias model (as these parameters should represent little-to-no effect of probability or reward). Data simulated from the bias model does not utilize reward or probability in the simulations. As such, data simulated from the bias model should be accurately recovered by the bias model at high rates regardless of the parameters used to generate the data. The proportion of surrogate datasets best-fit by each model are shown in Table S8. Using our model comparison procedure, surrogate data generated from the bias model was correctly identified as coming from the bias model at high rates in all groups (95-97%) Whether or not surrogate data generated from the SV models were correctly identified was again dependent on the parameter values used to generate the data. When using parameter values from participants best-fit the SV models, the correct model was identified in 83% of surrogate datasets for the reward only model and 87% of surrogate datasets for the full SV model. We emphasize the following points from these analyses:

1. Data that is simulated from the bias model, and thus does not utilize reward and probability to simulate choices, is very rarely recovered by the more complex models (Table S8). Participants who truly show no modulation of choice based on reward or probability should be correctly identified by the bias model at very high rates.
2. When data is simulated from the SV model with $h = 0$, and therefore does not utilize probability to simulate choices, the reward only SV model is the best-fitting model for the majority of cases (excluding $k=0$ “no discounting” and $k>4.5$ “high discounting”, which are best fit by the bias model and discussed above).

3. At reasonable values of *h* and *k* (i.e. some discounting, but low enough parameter values that subjective values of the highest rewards remain positive), the full subjective value model is also recovered at very high rates (Table S5). For the parameter values of participants best-fit by the reward and full SV models, the generating model is recovered in 83 and 87% of cases, respectively (Table S8).
4. **Medication Effects Measures used in each sample**

The specific medications reported by participants in each sample are in Table S9. The proportion of subjects taking typical and atypical medications was very similar across model-fit groups (Figure S2)—differences were not significant for either sample (*p*'s>.8), however, we had very few participants taking first-generation antipsychotics.

Participants taking risperidone were most frequently best-fit by the bias model (.52) followed by reward only model (.29) and full SV model (.19). Participants taking clozapine were most often best-fit by the bias model (.45), followed by the reward only (.27) and full SV models (.27). While the group taking clozapine showed a slight decrease in proportion best-fit by the bias model relative to those taking risperidone (and the general sample), the difference between these groups was not significantly different, X2 (2, N=32)=.297, p=.862.

EBDM Within Model-Defined Sub-Groups

As a final set of analyses, we sought to examine differences between patients and controls within each of the three best-fitting model sub-groups (full-SV, reward only, and bias). Within the participants best-fit the SV model, the patient x reward, patient x probability, and main effects of patient group were all non-significant (*ps*>.2), suggesting that these individuals with schizophrenia allocated effort in a manner that was very similar to healthy controls. This group exhibited very strong main effects of reward $F(3,276)=240.22$, $p<.001$, $\eta_p^2=.723$ 90% CI [.66,.75], and probability $F(1,92)=351.95$, $p<.001$, $\eta_p^2=.793$ 90% CI [.72,.83], and a strong probability x reward interaction, $F(3,276)=11.52$, $p<.001$, $\eta_p^2=.111$ 90% CI [.053,.16].

Within the reward-only SV group, we again observed a very strong main effect of reward, $F(3,156)=198.20$, $p<.001$, $\eta_p^2= .792$ 90% CI [.74,.82], and non-significant effects of probability, ($p=.411$), patient group ($p = .150$), probability x reward interaction ($p=.573$), and probability x patient group interaction ($p = .422$). We also observed a significant reward x patient interaction, $F(3,156)=3.44$, $p=.018$, $\eta_p^2=.062$ 90% CI [.006,.12]. Within individuals best-fit by the reward-only SV model, patients with schizophrenia selected the high-effort option slightly less often (M=.50) than healthy control participants (M=.58). The difference between patients and controls was localized to the second reward bin $t(52)=2.18$, $p=.034$, $d=.603$ 90% CI [.14,1.07] and was not significant at any other reward bin (ps > .1).

Among participants who were best-fit by the bias model, we observed a non-significant effect of patient group ($p = .119$), patient x probability ($p=.708$) and patient x reward ($p=.515$) interactions. Patients in this group selected the high-effort option slightly less (M=.49) than healthy controls (M=.62).

Thus, when examining behavior among individuals who use a similar strategy (i.e. same best-fitting model), we identified one group of participants with schizophrenia who performed very similarly to healthy controls and who used reward and probability information to guide choice, a second group who showed strong effects of reward and comparatively weaker effect of probability, and a third group that showed very little behavioral variation as a function of available information. Only the reward-only group suggested a possible interaction between patient group and reward, however, this group did not show differences at the highest reward levels.

Table S1: Parameter and fit statistics for included models

	Control			Schizophrenia		
	Bias	Reward	Full SV	Bias	Reward	Full SV
a	.42 (.26)	-	-	.49 (.30)	-	-
k	-	2.58 (2.78)	1.63 (2.18)	-	3.26 (3.23)	2.38 (2.90)
h	-	-	2.28 (3.15)	-	-	2.59 (3.72)
t	-	11.21 (28.63)	18.68 (34.49)	-	16.47 (34.24)	20.77 (37.10)
BIC	53.94 (22.52)	47.42 (20.68)	44.14 (19.28)	48.57 (26.13)	45.08 (22.86)	45.53 (21.37)
pseudo-*r*2	0.26	0.41	0.52	0.33	0.44	0.49

Note: Standard deviations in parentheses.

***Table S2*:** Negative symptoms, demographic characteristics, and cognitive functioning in model-defined groups of participants with schizophrenia.

	Best-fitting Model			
	Bias	SV-Reward	SV-Full	*F*
Sample 1				
% Male	55.1%%	71.40%	53.80%	
SANS Negative Symptoms	8.76 (2.96)	8.64 (3.27)	5.85 (3.13)	4.36*
SANS Anhedonia	2.55 (.57)	2.64 (1.34)	2.46 (1.13)	0.12
SANS Avolition	3.14 (.88)	3.00 (.68)	2.46 (1.13)	2.47
SAPS Positive Symptoms	4.45 (2.76)	3.86 (3.13)	2.69 (2.06)	1.87
SANS Disorganization	4.00 (3.13)	2.79 (2.55)	2.62 (2.33)	1.48
WAIS Matrix Reasoning	8.48 (3.56)	10.36 (3.08)	11.69 (2.93)	4.59*
Age	41.28 (7.78)	35.17 (8.38)	37.71 (7.41)	3.06
Education	12.21 (1.80)	13.07 (1.64)	14.69 (2.32)	7.73**
Reaction Time	1.36 (.73)	1.57 (.36)	1.40 (.40)	0.63
Completion Rate	.92 (.12)	.98 (.03)	.98 (.03)	2.79
Sample 2				
% Male	65.20%	94.40%	60.00%	
PANSS - Negative Symptoms	16.09 (7.28)	17.67 (6.94)	14.73 (6.44)	1.02
PANSS - Positive Symptoms	17.07 (6.78)	20.78 (8.48)	19.17 (7.62)	1.84
CAINS - Motivation and Pleasure (MAP)	16.07 (8.20)	16.61 (4.16)	14.27 (6.39)	0.83
CAINS - motivation items	1.80 (.93)	1.97 (.57)	1.60 (.84)	1.16
CAINS - pleasure items	1.77 (.96)	1.74 (.56)	1.57 (.78)	0.52
MCCB Composite	28.76 (12.70)	30.22 (6.71)	36.73 (12.73)	4.27*
MCCB Speed of Processing	33.02 (13.90)	38.17 (6.63)	44.03 (11.71)	7.49**
MCCB Attention/Vigilance	36.59 (12.46)	39.11 (11.15)	37.53 (13.27)	0.27
MCCB Working Memory	34.83 (10.23)	37.22 (7.19)	40.53 (10.31)	3.11*
MCCB Verbal Learning	38.74 (9.04)	37.06 (6.18)	43.70 (10.33)	3.92*
MCCB Visual Learning	37.24 (12.35)	37.17 (11.81)	43.27 (13.10)	2.39
MCCB Reasoning and Problem Solving	43.67 (9.38)	43.39 (9.93)	47.10 (12.34)	1.14
MCCB Social Cognition	35.22 (12.46)	32.56 (11.28)	37.60 (9.86)	1.11
Age	50.33 (11.55)	47.78 (11.82)	46.97 (11.49)	0.85
Education	13.11 (1.74)	13.22 (2.05)	13.43 (1.85)	0.28
Reaction Time	2.65 (1.36)	2.47 (1.07)	4.05 (1.71)	10.53**
Completion Rate	.93 (.10)	.94 (.09)	.94 (.12)	0.09

Note. Standard deviations in parentheses. SANS = Scale for the Assessment of Negative Symptoms (Andreasen, 1989); WAIS = Wechsler Adult Intelligence Scale (Wechsler, 2014); MCCB = MATRICS Consensus Cognitive Battery (Green & Nuechterlein, 2004); PANSS = Positive and Negative Syndrome Scale (Kay et al., 1987); CAINS = Clinical Assessment Interview for Negative Symptoms (Kring et al., 2013). In Sample 2, RT calculation excluded any RT greater than 60 seconds (9 trials total). Years of education was not reported for one subject in Sample 2. * $p < .05$, ** $p < .01$.

Table S3: Statistics for included and excluded variables in stepwise regressions

Sample 1: Predicting delta-BIC	*t*	*p*	Sample 1: Predicting *k (*best-fit by SV models) *t*	*p*
Included Variables			*Included Variables*	
WAIS Matrix	3.583	0.001	SANS Avolition	2.34	0.023
Excluded Variables			*Excluded Variables*	
Education	1.71	0.091	WAIS Matrix	-0.237	0.813
Age	-1.645	0.103	Education	0.609	0.545
Sex	0.18	0.858	Age	-0.072	0.943
SANS Negative	-0.411	0.682	Sex	-0.182	0.856
SAPS Positive	-0.148	0.883	SANS Negative	0.653	0.517
Patient	0.032	0.975	SAPS Positive	-0.691	0.492
SANS Avolition	0.074	0.942	Patient	0.558	0.579
SANS Anhedonia	-0.226	0.821	SANS Anhedonia	-1.187	0.241
Sample 2: Predicting delta-BIC			Sample 2: Predicting *k (*best-fit by SV models)	
Included Variables			*Included Variables*	
MCCB Composite	3.553	0.001	CAINS Motivation	2.109	0.04
Excluded Variables			*Excluded Variables*	
Education	0.159	0.874	Education	-0.815	0.419
Age	-0.909	0.366	Age	1.435	0.158
Sex	0.646	0.52	Sex	0.573	0.569
PANSS Negative	0.109	0.913	PANSS Negative	0.732	0.468
PANSS Positive	0.671	0.504	PANSS Positive	0.481	0.633
CAINS Motivation	0.124	0.902	CAINS Pleasure	0.72	0.476
CAINS Pleasure	-0.689	0.493	MCCB Composite	-0.073	0.942
Sample 1: Predicting *k*					
Included Variables					
SANS Avolition	2.981	0.004			
Excluded Variables					
WAIS Matrix	1.259	0.211			
Education	0.606	0.546			
Age	-1.019	0.311			
Sex	-1.118	0.267			
SANS Negative	-0.219	0.827			
SAPS Positive	0.546	0.586			
Patient	0.716	0.476			
SANS Anhedonia	-1.442	0.153			

Table S4: Parameter recovery. Correlation coefficients between best-fitting parameters and corresponding parameters recovered from simulated data.

	k	*t*	*h*	fit
All Participants	0.917**	0.944**	0.835**	0.982**
Schizophrenia	0.919**	0.932**	0.815**	0.981**
Healthy Controls	0.909**	0.963**	0.883**	0.985**
Sample 1	0.915**	0.971**	0.757**	0.960**
Sample 2	0.917**	0.932**	0.859**	0.998**

**p<.001

Table S5: SV model recovery parameter matrix showing the proportion of datasets simulated from the full SV model that were recovered by the full SV model at different combinations of parameters k and h. Rows represent different values of the h parameter, while columns indicate different values of the k parameter. Inverse temperature parameter *t* for all cells is 30. Note that the full SV model is recovered at very high rates for moderate parameter values (See Results: Model Recovery for full discussion). Proportions recovered by the reward only model and bias model are shown in Table S6 and Table S7, respectively.

	Simulated from full SV model: proportion recovered as best-fit by the full SV model										
	k parameter										
h	**0.00**	**0.50**	**1.00**	**1.50**	**2.00**	**2.50**	**3.00**	**3.50**	**4.00**	**4.50**	**5.00**
0.00	0.00	0.08	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00
0.50	0.02	0.60	0.70	0.92	0.98	1.00	1.00	1.00	0.98	0.00	0.00
1.00	0.06	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.06	0.00	0.00
1.50	0.18	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00
2.00	0.28	1.00	1.00	1.00	1.00	1.00	1.00	0.28	0.00	0.00	0.00
2.50	0.44	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00
3.00	0.62	1.00	1.00	1.00	1.00	1.00	0.78	0.00	0.00	0.00	0.00
3.50	0.70	1.00	1.00	1.00	1.00	1.00	0.04	0.00	0.00	0.00	0.00
4.00	0.56	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
4.50	0.74	1.00	1.00	1.00	1.00	0.56	0.00	0.00	0.00	0.00	0.00
5.00	0.66	1.00	1.00	1.00	1.00	0.06	0.00	0.00	0.00	0.00	0.00
5.50	0.82	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
6.00	0.86	1.00	1.00	1.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00
6.50	1.00	1.00	1.00	1.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00
7.00	0.94	1.00	1.00	1.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00
7.50	0.98	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8.00	0.98	1.00	1.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8.50	0.98	1.00	1.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9.00	1.00	1.00	1.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9.50	1.00	1.00	1.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10.00	0.98	1.00	1.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. Warmer colors indicate a higher proportion of surrogate data sets were classified by this model.

Table S6: SV model recovery parameter matrix showing the proportion of datasets simulated from the full SV model that were recovered by the reward SV model at different combinations of parameters *k* and *h*. Rows represent different values of the *h* parameter, while columns indicate different values of the *k* parameter. Inverse temperature parameter *t* for all cells is 30. Note that the reward-only model is often the best-fitting model when *h* = 0 (See Results: Model Recovery for full discussion). Proportions recovered by the full SV model and bias model are shown in Table S5 and Table S7, respectively.

	Simulated from full SV model: proportion recovered as best-fit by the reward SV model										
	k parameter										
h	**0.00**	**0.50**	**1.00**	**1.50**	**2.00**	**2.50**	**3.00**	**3.50**	**4.00**	**4.50**	**5.00**
0.00	0.00	0.92	0.92	1.00	1.00	1.00	1.00	1.00	1.00	0.44	0.00
0.50	0.00	0.40	0.30	0.08	0.02	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. Warmer colors indicate a higher proportion of surrogate data sets were classified by this model.

Table S7: SV model recovery parameter matrix showing the proportion of datasets simulated from the full SV model that were recovered by the bias model at different combinations of parameters *k* and *h*. Rows represent different values of the *h* parameter, while columns indicate different values of the *k* parameter. Inverse temperature parameter *t* for all cells is 30. Note that the bias model is often the best-fitting model when the parameter values are more extreme (See Results: Model Recovery for full discussion). Proportions recovered by the full SV model and reward only models are shown in Table S5 and Table S6, respectively.

Simulated from full SV model: proportion recovered as best-fit by bias model											
	k parameter										
h	**0.00**	**0.50**	**1.00**	**1.50**	**2.00**	**2.50**	**3.00**	**3.50**	**4.00**	**4.50**	**5.00**
0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.42	1.00
0.50	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	1.00	1.00
1.00	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	1.00	1.00
1.50	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00
2.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.72	1.00	1.00	1.00
2.50	0.56	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
3.00	0.38	0.00	0.00	0.00	0.00	0.00	0.22	1.00	1.00	1.00	1.00
3.50	0.30	0.00	0.00	0.00	0.00	0.00	0.96	1.00	1.00	1.00	1.00
4.00	0.44	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00
4.50	0.26	0.00	0.00	0.00	0.00	0.44	1.00	1.00	1.00	1.00	1.00
5.00	0.34	0.00	0.00	0.00	0.00	0.94	1.00	1.00	1.00	1.00	1.00
5.50	0.18	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
6.00	0.14	0.00	0.00	0.00	0.02	1.00	1.00	1.00	1.00	1.00	1.00
6.50	0.00	0.00	0.00	0.00	0.68	1.00	1.00	1.00	1.00	1.00	1.00
7.00	0.06	0.00	0.00	0.00	0.94	1.00	1.00	1.00	1.00	1.00	1.00
7.50	0.02	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8.00	0.02	0.00	0.00	0.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8.50	0.02	0.00	0.00	0.30	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9.00	0.00	0.00	0.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9.50	0.00	0.00	0.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10.00	0.02	0.00	0.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note. Warmer colors indicate a higher proportion of surrogate data sets were classified by this model.

***Table S8*:** Model recovery by group. Proportion of datasets recovered by each model ("Recovering Model") for surrogate data generated from the bias, reward, and full SV models ("Generating Model"). The best-fitting parameters of study participants were used to generate the surrogate data. Results are grouped by the best-fitting model of the participants whose parameters were used to generate the surrogate data ("Participant Group"). For ease of reference, matches between best-fitting model and model used to generate the data are highlighted in gray, with matched recovering model in bold.

Participant Group	Generating Model	Recovering Model		
		Bias	Reward SV	Full SV
Bias	Bias	**0.97**	0.01	0.01
	Reward SV	0.78	0.14	0.08
	Full SV	0.77	0.08	0.15
Reward only	Bias	0.95	0.03	0.02
	Reward SV	0.06	**0.83**	0.12
	Full SV	0.06	0.76	0.17
Full SV	Bias	0.96	0.02	0.02
	Reward SV	0.26	0.59	0.15
	Full SV	0.06	0.07	**0.87**

Table S9: Medication breakdown in each sample.

Sample 1		*Sample 2*	
Medication	n	Medication	n
Aripiprazole Monotherapy	7	Aripiprazole Monotherapy	15
Aripiprazole + Risperidone	1	Aripiprazole + Quetiapine	3
Asenapine Monotherapy	1	Aripiprazole + Risperidone	1
Clozapine Monotherapy	3	Aripiprazole + Olanzapine	2
Clozapine + Fluphenazine	1	Asenapine Monotherapy	1
Clozapine + Paliperidone	2	Chlorpromazine Monotherapy	1
Haloperidol Monotherapy	3	Clozapine Monotherapy	8
Haloperidol + Olanzapine	1	Clozapine + Fluphenazine	1
Haloperidol + Quetiapine	1	Clozapine + Olanzapine	1
Iloperidone Monotherapy	1	Clozapine + Risperidone	2
Olanzapine Monotherapy	3	Fluphenazine Monotherapy	2
Olanzapine + Quetiapine	1	Fluphenazine + Risperidone	1
Paliperidone Monotherapy	3	Haloperidol Monotherapy	5
Paliperidone + Perphenazine	1	Iloperidone Monotherapy	4
Paliperidone + Quetiapine	1	Iloperidone + Quetiapine	1
Quetiapine Monotherapy	6	Lurasidone Monotherapy	2
Quetiapine + Risperidone	3	Olanzapine Monotherapy	4
Quetiapine + Ziprasidone	1	Olanzapine + Ziprasidone	1
Risperidone Monotherapy	6	Olanzapine + Quetiapine	1
Ziprasidone Monotherapy	4	Paliperidone Monotherapy	1
No medication	6	Perphenazine Monotherapy	1
		Quetiapine Monotherapy	10
		Quetiapine + Risperidone	1
		Risperidone Monotherapy	15
		Risperidone + Ziprasidone	1
		Thiothixene Monotherapy	1
		Ziprasidone Monotherapy	4
		Unknown	2
		No medication	2

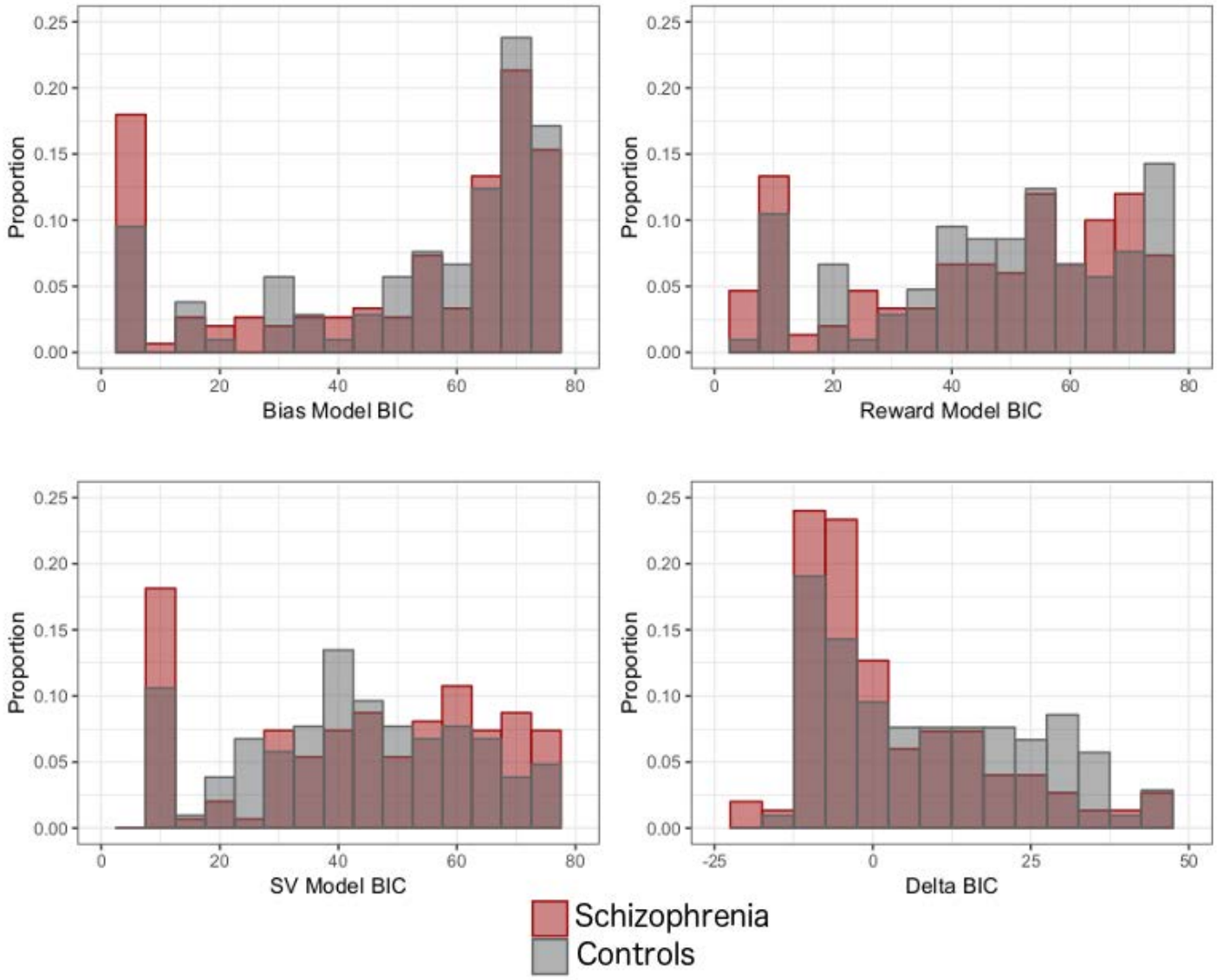

Figure S1: Model fit distribution in patients and controls. Y axis represents the proportion of cases in each group (schizophrenia or control).

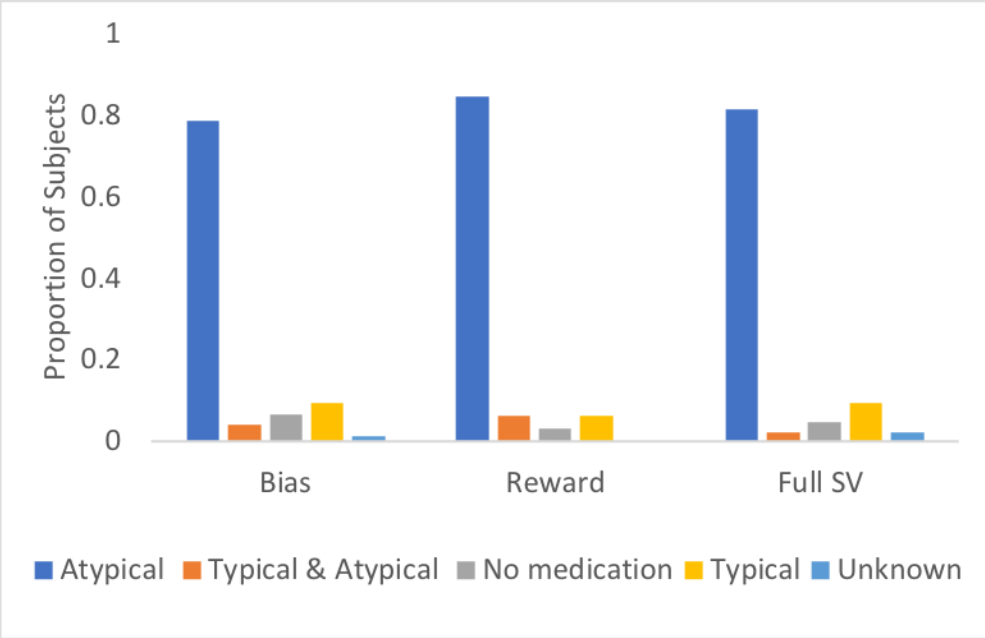

Figure S2: Medication effects. Proportion of subjects in each model-fit group taking atypical and typical medications.

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