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Supplementary Materials

Additional methods information

Computational model description

To model behavior on the AAC task described above, we adopted a Markov decision process model under the active inference framework (25, 26, 38). This approach requires writing down a generative model comprised of a few specific variables (that can each take a number of discrete values) and matrices describing the probabilistic relationships between those variables. The first two sets of variables are observations (*o*) and hidden states (*s*), where the relationships between these variables at a time (*t*) are described by a set of matrices referred to as **A** matrices – which encode the way that hidden states generate observations, $P(o_t|s_t)$. The probability that one hidden state will transition into another hidden state over time, $P(s_{t+1}|s_t)$, is encoded by a set of transition matrices referred to as **B** matrices (i.e., where these transitions also depend on selected actions, as described below). The degree to which an individual prefers (values) some observations over others is encoded within a matrix referred to as the **C** matrix, which, as explained further below, is technically modeled as a fixed set of prior expectations over observations, $P(o_t)$. Finally, a set of matrices referred to as **D** matrices encode the probability of starting out (e.g., at the beginning of each trial) in one hidden state vs. another, $P(s_{t=1})$.

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Belief updating in this class of models makes use of a set of variational update equations that approximate Bayesian inference. In these equations **D** is used as a prior for expected states (under each allowable sequence of actions or policy π) at the first time step (t = 1), while **B** provides priors over states at subsequent time steps in a trial, and these priors are integrated with the evidence that observations provide in favor of states, as specified by **A**:

$$\mathbf{s}_{\pi,1} = \sigma\left(\frac{1}{2}\left(\ln \mathbf{D} + \ln \mathbf{B} \cdot \mathbf{s}_{\pi,2}\right) + \ln \mathbf{A} \cdot o_t\right)$$

$$\mathbf{s}_{\pi,t} = \sigma\left(\frac{1}{2}\left(\ln \mathbf{B}\,\mathbf{s}_{\pi,t-1} + \ln \mathbf{B} \cdot \mathbf{s}_{\pi,t+1}\right) + \ln \mathbf{A} \cdot o_t\right)$$

Please note that when the dot (·) notation is applied to matrices in these and other model equations, this indicates transposed matrix multiplication.

To implement decision-making in this class of models requires that one write down the set of allowable policies that can be selected by the model. Technically, each action available at a given time point corresponds to a particular transition matrix (i.e., one of several **B** matrices) that defines a state transition under the control of the simulated individual (the "agent") described by the model, $P(s_{t+1}|s_t, \pi)$, such that each allowable policy corresponds to the selection of a sequence of state transitions. The impact of the agent's model on policy selection is also regulated by an expected precision term (γ) that can be thought of as encoding the agent's confidence in its action model – that is, confidence in the ability to select the best action based on current beliefs. When expected precision is

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high, policy selection is strongly determined by a posterior distribution over policies (i.e., a distribution specifying inferred policy values, described further below); when expected precision is low, this attenuates how sensitive an agent is to differences in the value of different policies during decision-making, and tends to promote behavior that appears more inconsistent, as it corresponds to higher uncertainty in decision-making. The model includes a prior over expected precision (β), which is formally the 'rate' parameter for a standard Gamma prior over the expected precision (γ). That is:

$$P(\gamma) = \Gamma(1, \beta).$$

The probability of a policy being selected is in turn determined by the observations it is expected to lead to and how much they diverge from preferred observations (the prior preference distribution defined by the **C** matrix). Posterior policy probabilities can be inferred based on the following equation:

$$\pi = \sigma(-\gamma G_\pi - F_\pi)$$

Here *F* and *G* refer to the free energy and expected free energy of a policy (respectively), where lower values of each promote selection of the corresponding policy. *F* can be thought of as encoding the accuracy of updated model predictions, while also taking into account how much prior beliefs need to be revised to reach high predictive accuracy. *G* is a measure of the divergence between actual and preferred observations, while also taking into how much a policy is expected to reduce uncertainty about states:

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$$\mathbf{F}_{\pi} = \sum_{t} \mathbf{s}_{\pi,t} \cdot \left(\ln \mathbf{s}_{\pi,t} - \frac{1}{2} \left(\ln \mathbf{B}\, \mathbf{s}_{\pi,t-1} + \ln \mathbf{B} \cdot \mathbf{s}_{\pi,t+1} \right) - \ln \mathbf{A} \cdot o_t \right)$$

$$\mathbf{G}_{\pi} = \sum_{t} \left(\mathbf{o}_{\pi,t} \cdot \left(\ln \mathbf{o}_{\pi,t} - \ln \mathbf{C} \right) - diag\left(\mathbf{A} \cdot \ln \mathbf{A} \right) \cdot \mathbf{s}_{\pi,t} \right)$$

Policies with higher probability will therefore better minimize the divergence between actual and preferred observations while also minimizing uncertainty. Actions are then chosen by sampling from the resulting posterior distribution over policies.

In the active inference scheme, approximately Bayes optimal inference is performed using standard variational message passing algorithms that minimize variational free energy, which, as described above, is an approximate means of minimizing the divergence between expected and preferred observations (39, 40). For a more detailed description and derivation of the associated belief update equations, see (24-26); here we implement these updates using the spm_MDP_VB_X.m routine freely available within the DEM toolbox implemented within the SPM12 software package (Wellcome Trust Centre for Neuroimaging, London, UK, http://www.fil.ion.ucl.ac.uk/spm).

To model the AAC task, one must therefore write down the sets of observations, hidden states, policies, and associated matrices that are sufficient to generate an individual's behavior during the task. Here, we included three categories of observations, corresponding to the observed position on the runway (10 possible observations, corresponding to a "starting" position and each of the nine positions on the runway that could be chosen), the task condition (five possible observations, corresponding to the five

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trial types), and the stimulus observed at the end of each trial (seven possible observations: a "starting" observation, negative affective stimulus + 0 points, positive affective stimulus + 0 points, positive affective stimulus + 2 points, negative affective stimulus + 2 points, negative affective stimulus + 4 points, and negative affective stimulus + 6 points). We included two categories of hidden states, corresponding to the individual's beliefs about their position on the runway and beliefs about the trial type. The mappings (**A** matrices) from beliefs about runway position and beliefs about trial type to observed positions and observed trial types (respectively) were specified as identity matrices, such that there was no uncertainty about the trial type or runway position. The **A** matrix specifying the mapping from beliefs about runway positions (columns in the matrix presented below) to observable stimuli (rows in the matrix presented below) defined the probabilities of observing each possible stimulus combination conditional on both the runway position and the trial type. For example, under the "avoid threat" (AV) trial type, the mapping from the runway positions to the different stimuli was as follows (columns = states, rows = observations):

$$P\left(o_{stimuli} \middle| s_{positions}, s_{trial\ type} = \text{AV}\right) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 9/10 & 8/10 & 7/10 & 6/10 & 5/10 & 4/10 & 3/10 & 2/10 & 1/10 \\ 0 & 1/10 & 2/10 & 3/10 & 4/10 & 5/10 & 6/10 & 7/10 & 8/10 & 9/10 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Rows from top to bottom correspond to: starting observation, negative affective stimulus + 0 points, positive affective stimulus + 0 points, positive affective stimulus + 2 points, negative affective stimulus +

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2 points, negative affective stimulus + 4 points, negative affective stimulus + 6 points. Thus, this matrix says that, under the AV trial type, the closer one was to the left side of the runway the higher the probability of observing the negative affective stimulus + 0 points, whereas the opposite mapping was true for observing the positive affective stimulus + 0 points. It also says that, under the AV trial type, the probability of observing all other possible stimulus combinations was 0. Analogous matrices defined the probabilities associated with each of the other trial types, which are depicted in **Figure 2** of the main manuscript.

The hidden states corresponding to runway positions were under the control of the agent, such that there was one **B** matrix encoding a transition from the starting state to each of the nine positions, corresponding to nine allowable one-step policies. The single **B** matrix that was specified for the other hidden state category (corresponding to trial types) was an identity matrix, encoding the belief that trial type remained stable within each trial. The **C** matrix was specified such that the value assigned to each possible stimulus observation was determined by three parameters corresponding to the subjective value of the positive affective stimulus, the subjective value of the negative affective stimulus, and the subjective value assigned to each point that could be won during the task. Here, we chose to fix the value of the positive affective stimulus at an "anchor" value of $\ln P(o) = 0$ and set the value of each point to $\ln P(o) = 1$ (i.e., $\ln P(o) = 2$ when winning 2 points, etc.). In other words, we quantified subjective value in terms of natural units – associating each point with a natural unit. This was motivated by the fact that the number of points ranged from 0 to 6. This covers the natural range of prior

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preferences, when interpreted in terms of log probabilities. We then estimated the value (subjective aversiveness) of the negative affective stimulus. This parameter indicated the "emotional conflict" (EC) – that is, the relative expected aversiveness of the affective stimuli relative to the expected (subjective) reward value assigned to each point. The *t* = 2 column in the **C** matrix specifying preferences over outcomes was therefore as follows:

$$lnP(o_{t=2}) = \boldsymbol{C}_{t=2} = [-EC \quad 0 \quad 2 \quad -EC+2 \quad -EC+4 \quad -EC+6]'$$

From left to right, this assigns value to observting the negative stimulus, the positive stimulus, the positive stimulus + 2 points, the negative stimulus + 2 points, the negative stimulus + 4 points, and the negative stimulus + 6 points.

The **D** matrix for the hidden state category corresponding to runway positions assigned a probability of 1 to starting within the starting state at the beginning of each trial and 0 otherwise, [1 0 0 0 0 0 0 0 0 0]', whereas the **D** matrix for the hidden state category corresponding to trial types assigned equal probability to each trial type, [.2 .2 .2 .2 .2]', reflecting the belief that no trial type was more likely to occur than any other. As mentioned above, prior policy precision (β) was not fixed in advance, but was also estimated for each individual.[1]

[1] Technically, we did fix a related inverse temperature parameter (α) for action selection that is included in active inference models to a value of 16, which allowed for plausible levels of indeterminacy in selecting an action after inferring posterior policy values.

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Our computational phenotyping approach used Bayesian inference at two levels (38). First, each participant's responses were modeled under ideal Bayesian assumptions – using the MDP formulation of choice behavior described previously. We then used Variational Bayes to estimate each participant's prior beliefs that maximized the likelihood of their responses, as described in (17). In other words, the observation model for estimating subject-specific preferences and precision was based on the assumption that subjects were using (active) Bayesian inference. In this setting, active inference can be seen as a generalization of Bayesian decision theory that replaces the expected value or utility with expected log evidence or marginal likelihood for a generative model of the task at hand (17). Technically, this means that subjective responses are sampled from their posterior beliefs about the best course of action, where these posterior beliefs depend upon their prior preferences about the consequences of a decision – and the information gain afforded by their actions. This posterior distribution over behavioral responses can then be used to assess the likelihood of responses under different prior beliefs. We optimized these preferences (and precision of posterior beliefs about policies) using this likelihood and standard variational Laplace (39).

This estimation approach has the advantage of preventing overfitting, due to the greater cost it assigns to moving parameters farther from their prior values. In this case, we chose to estimate two parameters (EC, β), which required setting prior means and prior variances for each parameter. The prior variance was set to a high precision value of 2^{-2} for each parameter (i.e., deterring overfitting), and the prior means (specified as lognormal priors) were set as follows: EC = 2 (made negative in the model) and β = 1. While other prior values could have been chosen, our decision for selecting these priors was

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motivated in part by initial simulations confirming that parameter values were recoverable under these prior values (described below). In addition, by selecting a prior value of (-)2 for EC, this also entailed that the task condition in which participants could observe the negative affective stimulus and receive the lowest number of (two) points would correspond to maximum conflict (i.e., these values would sum to 0). β = 1 is also a standard rate parameter often used for gamma priors.

We also considered two other models: a simpler 1-parameter model including no decision uncertainty term (only estimating EC), and a more complex 3-parameter model that fit the subjective value of the points as well. Formally, the simpler model simply removed the expected policy precision term (γ), such that posteriors over policies were simply:

$$\pi = \sigma(-G_\pi - F_\pi)$$

The more complex model formally adjusted the **C** matrix displayed above to include a parameter that scaled the value of each points (Pval) as follows:

$$lnP(o_{t=2}) = \boldsymbol{C}_{t=2}$$
$$= [-EC \quad 0 \quad 2 \times P_{val} \quad -EC + 2 \times P_{val} \quad -EC + 4 \times P_{val} \quad -EC + 6 \times P_{val}]'$$

We first assessed whether model parameters were recoverable within simulated data, while varying true parameter values and prior values during model estimation. We then assessed whether posterior parameter estimates reliably approached the true parameter values specified in the simulations. Parameter estimates for the 3-parameter model did not appear recoverable, and were dependent on

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prior values, due to the fact that only the relative value of the negative stimuli vs. points ultimately influenced behavior. Therefore, we did not use this model. In contrast, estimates from the simpler 1-parameter model did appear recoverable, as they reliably approached true values from different starting priors. However, Bayesian model comparison (based on (46, 47)) showed that this model performed worse than the 2-parameter model (protected exceedance probability = 1). Parameters were recoverable for the 2-parameter model (i.e., simulations confirmed that estimated parameter values approached true parameter values across a range of parameter value combinations), and this model was therefore selected for our further analyses. **Supplementary Results**

Relationship between model parameters and demographic variables in the full sample

The EC parameter was positively correlated with WRAT scores (r = .17, p < .001), and was higher in females than males (t(384) = 2.97, p = .003). The β parameter was positively correlated with age (r = .21, p < .001) and negatively correlated with WRAT scores (r = -.24, p < .001).

Model parameter group difference analyses in the full sample

With respect to EC, there was a main effect of sex (F(1,466) = 9.01, p = .003; higher EC in females), WRAT reading score (F(1,466) = 16.04, p < .001), and clinical group (F(2,466) = 3.30, p = .04), as well as group by age (F(2,466) = 3.49, p = .03) and group by sex (F(2,466) = 3.92, p = .02) interactions. Post-hoc comparisons revealed a positive relationship between WRAT score and EC (r = .17, p < .001) and that the SUD group had significantly lower EC values than HCs (t(92) = 3.17, p = .002, Cohen's d = 0.51; see **Figure**

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4 in the main text) and DEP/ANX ($t(352) = 3.40$, $p < .001$, $d = 0.34$; and see **Figure 4** in the main text). The interactions primarily reflected a greater difference in EC values between females than males (higher in females) in HCs than SUDs, and a positive relationship between EC and age in the DEP/ANX group vs. a negative relationship between EC and age in HCs (and no relationship between these variables in SUDs).

With respect to β (prior policy precision – reflecting expected decision uncertainty), our analyses revealed a significant effect of age ($F(1,466) = 24.29$, $p < .001$), WRAT Reading score ($F(1,466) = 33.83$, $p < .001$), and a trend effect of clinical group ($F(2,466) = 3.02$, $p = .049$), as well as group by age interaction (($F(2,466) = 3.48$, $p = .03$)). Further post-hoc inspection revealed that β was higher with age ($r = .21$, $p < .001$), and lower with greater WRAT Reading score ($r = -.25$, $p < .001$). β was significantly lower in HCs than in those with SUDs ($t(123) = 4.27$, $p < .001$) and those with DEP/ANX ($t(100) = 2.33$, $p = .02$). The DEP/ANX group also showed significantly lower values than those with SUDs ($t(336) = 2.78$, $p = .006$). The interaction reflected a stronger positive relationship between β and age in the DEP/ANX group than in HCs or SUDs.

Follow-up analyses separated by sex

In the full sample, when redoing the analyses separated by sex, the pattern of group differences in EC remained significant in females ($F(2,297) = 6.32$, $p = .002$) but not in males ($F(2,163) = 0.04$, $p = .96$). The pattern of group differences in β remained significant in males ($F(2,163) = 4.92$, $p = .008$) but not in females ($F(2,297) = 0.21$, $p = .81$).

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In the propensity matched sample, when redoing the analyses separated by sex, the pattern of group differences in EC remained significant in females ($F(2,169) = 3.19$, $p = .04$) but not in males ($F(2,101) = 0.03$, $p = 0.97$). The pattern of group differences in β remained significant in males ($F(2,101) = 4.95$, $p = .009$) but not in females ($F(2,169) = 0.59$, $p = .59$).

Standard descriptive analyses in the full sample

During AV trials, there was a main effect of age ($F(1,466) = 12.64$, $p < .001$; less avoidance of the negative images with older age), sex ($F(1,466) = 4.27$, $p = .04$; less avoidance in males), WRAT score ($F(1,466) = 75.50$, $p < .001$; greater avoidance with higher scores), and group ($F(1,466) = 9.41$, $p < .001$) on chosen runway position. Post-hoc comparisons revealed that HCs showed greater avoidance of the negative images than DEP/ANX ($t(173) = 3.88$, $p < .001$) and SUDs ($t(214) = 7.85$, $p < .001$). SUDs also avoided less than DEP/ANX ($t(274) = 5.04$, $p < .001$).

During APP trials, there was a main effect of age ($F(1,466) = 13.72$, $p < .001$; less approach with older age) and WRAT Reading score ($F(1,466) = 13.72$, $p < .001$; greater approach with higher scores) on chosen runway position.

During conflict (CONF2, CONF4, CONF6) trials, there was a main effect of sex ($F(1,466) = 6.86$, $p = .009$; greater avoidance in females) on chosen runway position, and a group by age ($F(1,466) = 3.23$, $p = .04$) and group by sex ($F(1,466) = 4.25$, $p = .01$) interaction. These interactions reflected greater avoidance in females in HCs and DEP/ANX, but greater avoidance in males in SUDs, as well as a positive relationship

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between avoidance and age in the DEP/ANX group vs. a negative relationship between avoidance and age in HCs (and no relationship between these variables in SUDs).

When accounting for age, sex, WRAT scores, and their interaction with group, there was no effect of group on RTs in the full sample. There was a main effect of age ($F(1,464) = 63.35$, $p < .001$; slower RTs with older age) and WRAT scores ($F(1,464) = 11.67$, $p < .001$; slower RTs with lower WRAT scores), as well as an interaction between age and group ($F(2,464) = 3.61$, $p = .03$). The interaction reflected positive correlations between age and RTs in DEP/ANX ($r = .44$, $p < .001$) and SUDs ($r = .22$, $p = .004$), but not in HCs ($r = .09$, $p = .5$).

Within-group analyses

We performed post-hoc within-group Pearson correlations between model parameters and symptom severity measures available within the T1000 dataset, including the DAST, PHQ-9, and OASIS, as well as scales from the Patient Reported Outcomes Measurement Information System (PROMIS) assessing depression and anxiety (41) and the Anxiety Sensitivity Index (ASI) (42). For these post-hoc analyses we only report findings with $p < .01$.

No significant relationships were observed within each group between model parameters and the continuous clinical measures tested (i.e., DAST, PHQ, OASIS, PROMIS anxiety and depression scales, STAI, and ASI).

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Post-hoc analyses of within-subject variability

Based on the group differences we observed in decision uncertainty, we subsequently chose to perform post-hoc analyses of descriptive measures of behavioral variability. While not examined in previous studies, differences in behavioral variability are implied by our modeling results. **Table S4** displays the within-subject SDs across trials by task condition and group comparisons. As can be seen there, within-subject choice variability in both the full and propensity-matched samples differed significantly between groups in a manner following the same pattern seen in the decision uncertainty parameter. Interestingly, these differences were primarily seen within the Avoid, Approach, and Conflict (6 points) conditions, suggesting decision uncertainty even in the absence of explicit conflict (or variable drives to approach reward or avoid punishment in general). The decision uncertainty parameter was also significantly correlated with within-subject SDs across conditions, as would be expected (see **Figure S3**).

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Table S1. Task-specific self-report questionnaire summary statistics (Mean (SD))

Full Sample	**HCs (N = 59)**	**DEP/ANX(N = 260)**	**SUDs (N = 159)**	**p value***
1. I found the POSITIVE pictures enjoyable:	4.93 (1.89)	5.05 (1.67)	5.09 (1.64)	0.98
2. The NEGATIVE pictures made me feel anxious Or uncomfortable:	4.39 (1.83)	4.66 (1.98)	4.08 (2.01)	0.07
3. I often found it difficult to decide which outcome I wanted:	2.05 (1.59)	2.48 (1.74)	2.72 (1.75)	0.41
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS:	4.42 (2.60)	4.65 (2.38)	5.08 (2.03)	0.12
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS:	3.17 (2.49)	3.00 (2.17)	2.86 (2.04)	0.41
6. When a NEGATIVE picture and sound were	5.56 (1.87)	**5.22 (1.94)****	**5.92 (1.55)****	**0.03****

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displayed, I kept my eyes open and looked at the picture:				
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself:	3.17 (1.98)	3.15 (2.01)	2.57 (1.76)	0..08
8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures	3.24 (1.82)	3.49 (2.03)	2.89 (1.94)	0.21
Propensity Matched	**HCs (N = 59)**	**DEP/ANX (N = 161)**	**SUDs (N = 56)**	**p value*** **
1. I found the POSITIVE pictures enjoyable:	4.93 (1.89)	5.06 (1.69)	4.86 (1.69)	0.97
2. The NEGATIVE pictures made me feel anxious Or uncomfortable:	4.39 (1.83)	**4.75 (1.88)****	**3.82 (2.03)****	**0.047****
3. I often found it difficult to decide which outcome I	2.05 (1.59)	2.52 (1.77)	2.77 (1.80)	0.08

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wanted:				
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS:	4.42 (2.60)	4.66 (2.39)	4.82 (2.20)	0.59
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS:	3.17 (2.49)	2.91 (2.12)	3.07 (2.11)	0.51
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture:	5.56 (1.87)	5.23 (1.96)	6.04 (1.48)	0.28
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself:	3.17 (1.98)	3.11 (2.00)	2.45 (1.72)	0.19
8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the	3.24 (1.82)	3.58 (2.07)	2.62 (1.79)	0.07

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pictures				

***All ratings were on a scale of 1-7. ANCOVAs included Age, Sex, WRAT score, and their interactions with group.**

**** indicates significant group difference within post-hoc two-sample t-tests**

*****In ANCOVAs including Sex and Sex by group interactions.**

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Table S2. Summary statistics for task reaction times (Mean (SD))

Full Sample	**HCs (N = 59)**	**DEP/ANX(N = 260)**	**SUDs (N = 159)**	**p values***
Average reaction time (overall)	1.20 (0.28)	1.30 (0.31)	1.31 (0.32)	0.34
Average reaction time (avoid condition)	1.14 (0.26)	1.28 (0.36)	1.31 (0.40)	0.12
Average reaction time (approach condition)	**1.24 (0.29)**	**1.42 (0.35)**	**1.46 (0.34)**	**0.003****
Average reaction time (conflict 2 condition)	1.22 (0.36)	1.28 (0.36)	1.30 (0.38)	0.85
Average reaction time (conflict 4 condition)	1.20 (0.35)	1.25 (0.35)	1.24 (0.36)	0.72
Average reaction time (conflict 6 condition)	1.22 (0.37)	1.28 (0.36)	1.25 (0.34)	0.77
Propensity Matched	**HCs (N = 59)**	**DEP/ANX (N = 161)**	**SUDs (N = 56)**	**p value*****
Average reaction time (overall)	1.20 (0.28)	1.28 (0.28)	1.29 (0.26)	0.13

Appendix 1 to Smith R, Kirlic N, Stewart J, et al. Greater decision uncertainty characterizes a transdiagnostic patient sample during approach-avoidance conflict: a computational modelling approach. *J Psychiatry Neurosci* 2020.

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Average reaction time (avoid condition)	**1.14 (0.26)**	**1.25 (0.33)**	**1.31 (0.40)**	**0.017****
Average reaction time (approach condition)	**1.24 (0.29)**	**1.38 (0.32)**	**1.44 (0.30)**	**<0.001****
Average reaction time (conflict 2 condition)	1.22 (0.36)	1.27 (0.34)	1.28 (0.33)	0.58
Average reaction time (conflict 4 condition)	1.20 (0.35)	1.23 (0.31)	1.22 (0.30)	0.71
Average reaction time (conflict 6 condition)	1.22 (0.37)	1.26 (0.34)	1.21 (0.28)	0.79

***In ANCOVAs including Age, Sex, WRAT Reading score, and their interactions with group.**

**** indicates both clinical groups are significant different than healthy controls within post-hoc two-sample t-tests**

*****In ANCOVAs including Sex and Sex by group interactions.**

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Table S3. Summary statistics for chosen runway position (Mean (SD))

Mean Chosen Runway Position by Trial Type† **Full Sample**	**HCs (N = 59)**	**DEP/ANX(N = 260)**	**SUDs (N = 159)**	**p values***
Avoid Condition	**9.57 (0.84)**	**8.99 (1.64)**	**8.01 (2.09)**	**<0.001*** **
Approach Condition	9.71 (0.78)	9.23 (1.48)	8.92 (1.50)	0.059
Conflict (2 points)	6.94 (3.20)	7.30 (2.85)	7.88 (2.31)	0.12
Conflict (4 points)	7.14 (3.28)	7.66 (2.79)	8.15 (2.25)	0.09
Conflict (6 points)	7.41 (3.26)	7.84 (2.77)	8.34 (2.19)	0.14
Propensity Matched	**HCs (N = 59)**	**DEP/ANX (N = 161)**	**SUDs (N = 56)**	**p values**** **
Avoid Condition	**9.57 (0.84)**	**9.18 (1.45)**	**8.11 (2.07)**	**<0.001*** **
Approach Condition	**9.71 (0.78)**	**9.16 (1.62)**	**8.88 (1.52)**	**0.007****
Conflict (2 points)	6.94 (3.20)	7.17 (2.93)	7.64 (2.53)	0.51

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Conflict (4 points)	7.14 (3.28)	7.54 (2.85)	7.79 (2.58)	0.36
Conflict (6 points)	7.41 (3.26)	7.70 (2.85)	8.06 (2.54)	0.49

† Higher values indicate greater approach behavior (i.e., toward the points). In the avoid condition, higher values indicate runway positions closer to the positive stimulus.

***In ANCOVAs including Age, Sex, WRAT Reading score, and their interactions with group.**

**** indicates both clinical groups are significant different than healthy controls within post-hoc two-sample t-tests**

***** indicates that all three groups are significantly different within post-hoc two-sample t-tests**

******In ANCOVAs including Sex and Sex by group interactions.**

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Table S4. Summary statistics for within-subject variability (SD) in chosen runway position (Mean (SD))

Standard Deviation in Chosen Runway Position by Trial Type **Full Sample**	**Healthy controls (N = 59)**	**Anxiety/depression (N = 260)**	**Substance use (N = 159)**	**P values***
Avoid Condition	**0.65 (0.96)**	**1.00 (1.18)**	**1.61 (1.21)**	**0.001*****
Approach Condition	**0.46 (0.90)**	**0.77 (1.12)**	**1.16 (1.20)**	**0.02*****
Conflict (2 points)	1.04 (1.21)	1.29 (1.21)	1.46 (1.18)	0.48
Conflict (4 points)	0.85 (1.01)	1.07 (1.17)	1.30 (1.17)	0.15
Conflict (6 points)	**0.83 (1.08)**	**1.09 (1.24)**	**1.42 (1.24)**	**0.04****

Appendix 1 to Smith R, Kirlic N, Stewart J, et al. Greater decision uncertainty characterizes a transdiagnostic patient sample during approach-avoidance conflict: a computational modelling approach. *J Psychiatry Neurosci* 2020.

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Propensity Matched	**Healthy controls (N = 59)**	**Anxiety/depression (N = 260)**	**Substance use (N = 159)**	**P values*******
Avoid Condition	**0.65 (0.96)**	**0.89 (1.14)**	**1.60 (1.16)**	**<0.001******
Approach Condition	**0.46 (0.90)**	**0.77 (1.14)**	**1.13 (1.19)**	**0.006****
Conflict (2 points)	1.04 (1.21)	1.25 (1.20)	1.39 (1.22)	0.23
Conflict (4 points)	0.85 (1.01)	1.09 (1.15)	1.26 (1.21)	0.09
Conflict (6 points)	**0.83 (1.08)**	1.08 (1.24)	**1.39 (1.23)**	**0.02**

***In ANCOVAs including Age, Sex, WRAT Reading score, and their interactions with group.**

**** indicates both clinical groups are significant different than healthy controls within post-hoc two-sample t-tests**

***** indicates that all three groups are significantly different within post-hoc two-sample t-tests**

****** indicates SUDs differ from both healthy controls and DEP/ANX**

*******In ANCOVAs including Sex and Sex by group interactions.**

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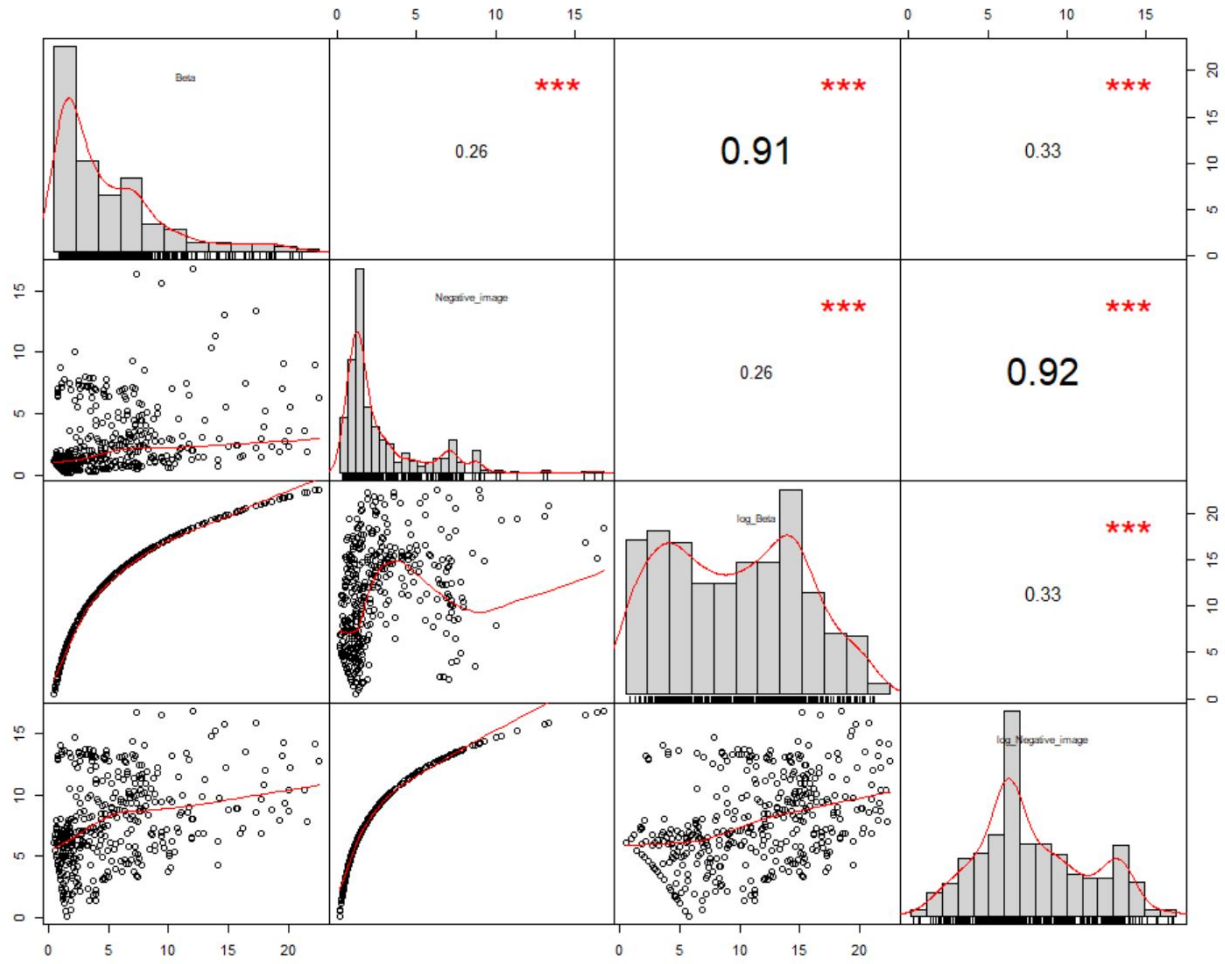

Figure S1*. Distributions and correlations between model parameters and their log transforms.*

Appendix 1 to Smith R, Kirlic N, Stewart J, et al. Greater decision uncertainty characterizes a transdiagnostic patient sample during approach-avoidance conflict: a computational modelling approach. *J Psychiatry Neurosci* 2020.

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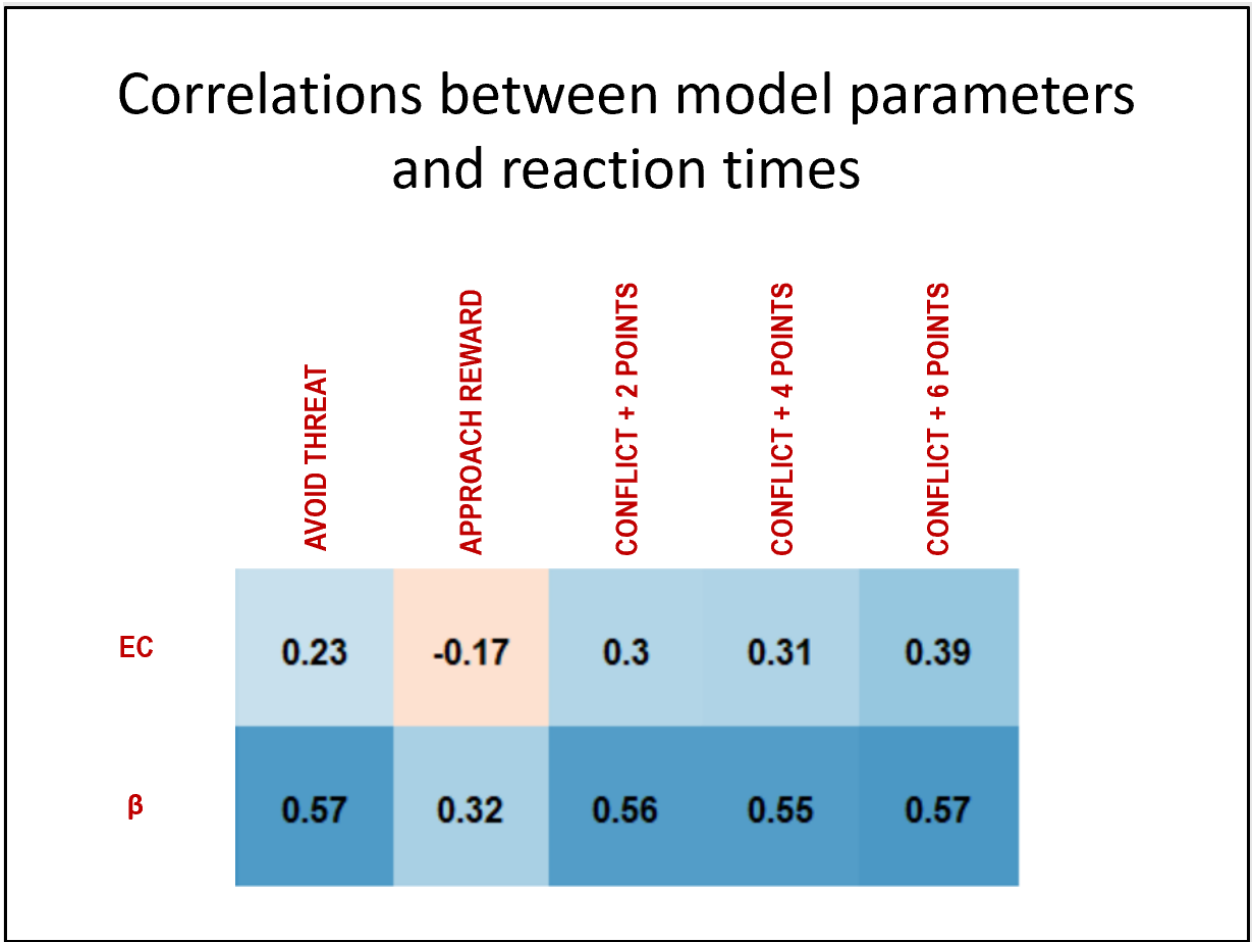

***Figure S2**. Pearson correlations between model parameter estimates and task reaction times in the full sample (per task condition).*

Appendix 1 to Smith R, Kirlic N, Stewart J, et al. Greater decision uncertainty characterizes a transdiagnostic patient sample during approach-avoidance conflict: a computational modelling approach. *J Psychiatry Neurosci* 2020.

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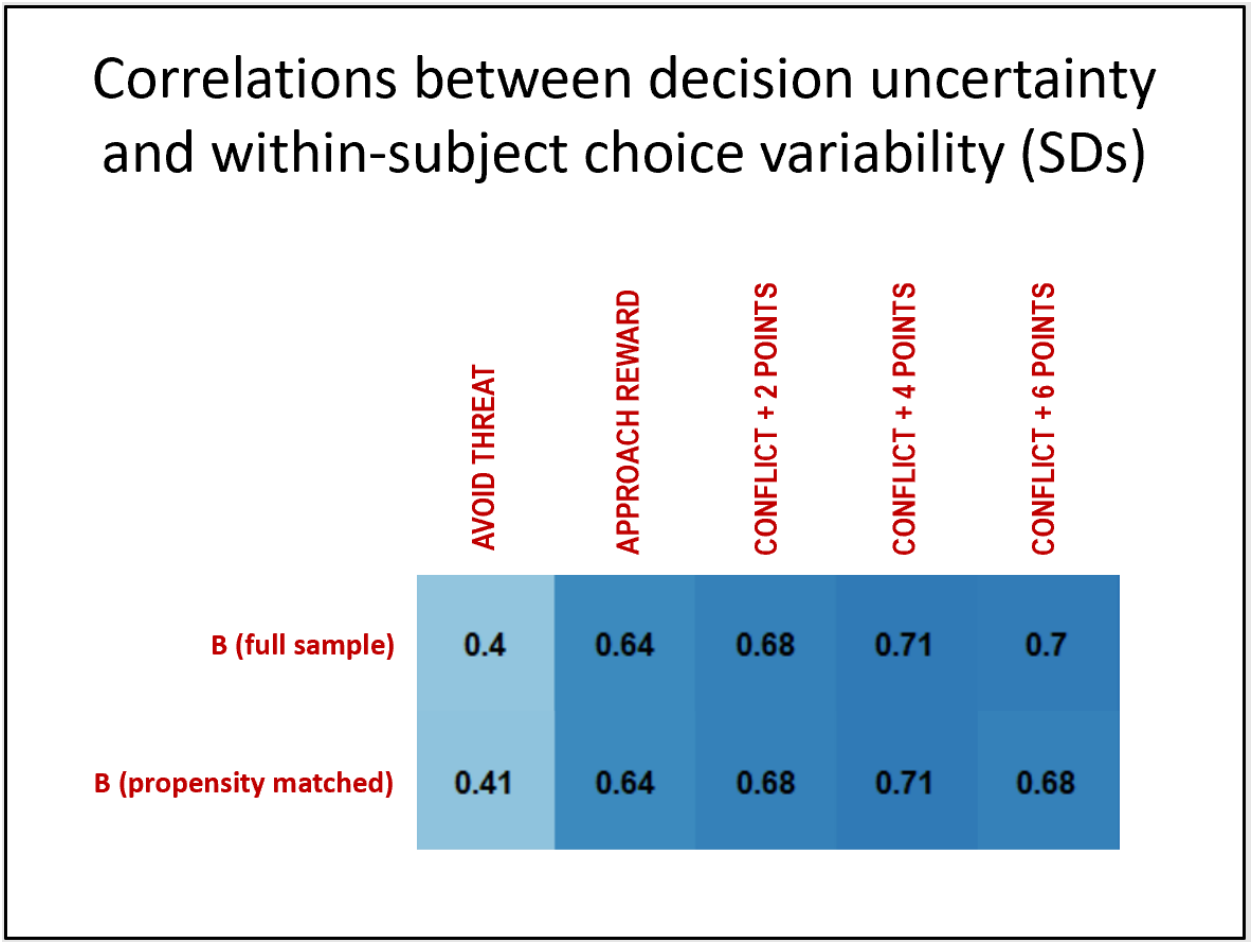

***Figure S3**. Pearson correlations between decision uncertainty parameter estimates (β) and within subject choice variability (per task condition).*