**Greater decision uncertainty characterizes a transdiagnostic patient sample during
approach-avoidance conflict: a computational modeling approach**

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Abstract

Background: Imbalances in approach-avoidance conflict (AAC) decision-making (e.g. sacrificing rewards to avoid negative outcomes) are considered central to multiple psychiatric disorders. We used computational modeling to examine two factors often not distinguished within descriptive analyses of AAC: decision uncertainty and sensitivity to negative outcomes vs. reward (emotional conflict).

Methods: A previously-validated AAC task was completed by 477 participants, including healthy controls (HCs; N=59), individuals with substance use disorders (SUDs; N=159) and individuals with depression and/or anxiety (DEP/ANX; N=260) disorders without SUDs. Using an active inference model, we estimated individual-level values for a model parameter (β) reflecting decision uncertainty as well as another reflecting emotional conflict. Analyses were also repeated in a subsample (N = 59 HCs, 161 DEP/ANX, 56 SUDs) propensity matched on age and general intelligence.

Results: The model showed high accuracy (72%). As further validation, parameters correlated with reaction times and self-reported task motivations in expected directions. emotional conflict further correlated with self-reported anxiety during the task ($r=0.32$, $p<0.001$), while decision uncertainty correlated with self-reported difficulty making decisions ($r=0.45$, $p<0.001$). Compared to HCs, both DEP/ANX and SUDs showed higher decision uncertainty in the propensity matched sample ($t=2.16$, $p = .03$; and $t=2.88$, $p = .005$, respectively), with analogous

results in the full sample; SUDs also showed lower emotional conflict in the full sample ($t=3.17$, $p=0.002$).

Limitations: This study is limited by clinical sample heterogeneity and an inability to examine learning.

Conclusions: These results suggest that reduced confidence in how to act, rather than increased emotional conflict, may explain maladaptive approach-avoidance behaviors in psychiatric disorders.

Keywords: approach-avoidance conflict; anxiety; depression; active inference; substance use; computational psychiatry.

Introduction

Imbalances in the decision to approach or avoid when both positive and negative consequences are expected (i.e., approach-avoidance conflict; AAC) is often problematic in mental health conditions (1). Individuals with depression and anxiety, for example, may choose to sacrifice participation in rewarding activities because they believe such activities will also lead to negative consequences (e.g., judgement, embarrassment; (2)). Individuals with substance use disorders (SUDs) also engage in costly drug-taking behaviors to avoid negative affect, and show impairment during decision-making on tasks that involve conflict between reward and punishment (reviewed in (3, 4)). A better understanding of the underlying factors contributing to avoidance-based decision-making may improve our understanding of these mental health

conditions and inform the development of treatments targeting the distinct factors relevant for individual patients (5).

There are several paradigms used to study AAC (for a review, see (6)), most of which create conflict between receiving monetary rewards and either monetary punishments (monetary-based conflict; (7, 8)), pain (pain-based conflict; (9)) or aversive affective stimuli (affect-based conflict; (10-13)). While often analyzed using more traditional behavioral measures, computational modeling has emerged as a promising new approach for studying AAC (14-19). Modeling allows for precise quantification of distinct information processing mechanisms that contribute to decision-making. For example, in a monetary-based conflict study (20), variations in a model parameter reflecting relative sensitivity to reward vs. punishment accounted for sex differences in avoidance (greater avoidance behavior in females), whereas greater sensitivity to punishment overall better accounted for the increased avoidance behavior observed in individuals with an inhibited temperament. In a pain-based conflict study (9), computational modeling also showed that sensitivity to reward-based benefits becomes increasingly attenuated as pain-based costs increased in aversiveness.

This approach has not yet been applied to affect-based conflict. Doing so may add clinical value, as anticipation of negative affect may be particularly important for understanding factors contributing to psychiatric disorders. To be clear, the distinction made here between affect-based conflict and pain-/monetary-based conflict is not meant to suggest that losing money or feeling the unpleasant sensation of pain does not involve affective responses (21). The distinction

motivating the use of affect-based tasks is one of maximizing ecological validity, where affective disorders more often involve avoidance of the more complex “emotional pain” induced by socio-emotional cues (e.g., social rejection, losing a job, death, etc.). The visual/auditory affect-based task stimuli used herein are designed to more closely match such cues (e.g., by depicting social interactions mirroring some of those cues) and the emotionally painful responses they evoke.

In this paper, we apply a computational modeling approach (22, 23) to study affect-based conflict. We demonstrate how this approach can separate two underlying components of conflict not thoroughly distinguished in traditional descriptive analyses: decision uncertainty and relative sensitivity to negative affective stimuli vs. reward (emotional conflict). Both uncertainty and threat sensitivity have potential relevance for psychiatric disorders. For example, poor decision-making in individuals with anxiety has been associated with high intolerance of uncertainty and risk aversion (24, 25), whereas suboptimal decision-making in depression appears more driven by attenuated responses to reward (26, 27). SUDs have also been associated with intolerance of uncertainty (28), and a reduced ability to incorporate uncertainty into reward learning during decision-making tasks (29). However, the distinct contributions of uncertainty versus threat/reward sensitivity on avoidance behavior have not been fully delineated.

Using a relatively large sample comprising healthy controls (HCs) without psychiatric symptomatology and a transdiagnostic sample of patients with depression and anxiety (DEP/ANX) and/or SUDs, we estimate model parameters reflecting decision uncertainty and emotional conflict using an affect-based AAC task (11, 12, 30). We hypothesized that relative to

HC, both psychiatric groups would exhibit greater uncertainty as well as greater emotional conflict during AAC.

Method

Participants

Participants for this analysis were identified from the first 500 participants of the Tulsa 1000 (T1000) (31), a naturalistic longitudinal study recruiting subjects based on the dimensional NIMH Research Domain Criteria framework. The T1000 study included a community-based sample of approximately 1000 individuals recruited through radio, electronic media, treatment center referrals, and word of mouth (this sample size was planned a priori; see (31) for a detailed justification based on the aims of the larger study). Participants were 18-55 years of age, screened on the basis of dimensional psychopathology scores: Patient Health Questionnaire (PHQ-9 (32)) ≥ 10 , Overall Anxiety Severity and Impairment Scale (OASIS (33)) ≥ 8 , and/or Drug Abuse Screening Test (DAST-10 (34)) score > 3 . HCs did not show elevated symptoms or psychiatric diagnoses. Participants were excluded if they (i) tested positive for drugs of abuse, (ii) met criteria for psychotic, bipolar, or obsessive-compulsive disorders, or reported (iii) history of moderate-to-severe traumatic brain injury, neurological disorders, or severe or unstable medical conditions, (iv) active suicidal intent or plan, or (v) change in medication dose within 6 weeks. Full inclusion/exclusion criteria are described in (31). The study was approved by the Western Institutional Review Board. All participants provided written informed consent prior to completion of the study protocol, in accordance with the Declaration of Helsinki, and were

compensated for participation. ClinicalTrials.gov identifier: #NCT02450240. For previous papers published from the larger T1000 dataset, see (35-45). Notably, none of these previous papers included analyses using the AAC task.

Given the heterogeneous clinical sample in the T1000 and its explicitly transdiagnostic focus, we divided participants into three groups consisting of HCs, those with SUDs, and those with DEP/ANX who did not have SUDs. Participants were grouped based on DSM-IV or DSM-5 diagnosis using the Mini International Neuropsychiatric Inventory (MINI) (46), and current analyses focused on groups of individuals with major depressive and/or co-morbid anxiety disorders (social anxiety, generalized anxiety, panic, and/or posttraumatic stress disorder; N=260), SUDs (recreational drugs excluding alcohol and nicotine, with or without comorbid depression and anxiety disorders; N=159), and HCs with no mental health diagnoses (N=59). See Table 1 for more details. As further described in (31), the T1000 study was built around the NIMH Research Domain Criteria (RDoC) framework which describes dimensions of pathology (47). Thus, the T1000 study specifically aimed in advance to recruit participants with these symptom profiles, with the aim of identifying transdiagnostic behavioral and neural phenotypes related to threat/reward processing, interoceptive processing, and cognitive functioning. While symptoms can be observed dimensionally, as in the case of symptom scales, we also sought to categorize participants according to diagnoses. These categories were developed prior to the current analyses and discussed in previous papers (35). While the T1000 also included individuals with eating disorders, these were excluded here due to small sample sizes. Mood/Anxiety disorders were categorized together for our analyses due to the high rates of

overlap in these diagnoses and due to there being very small sample sizes ($N = 19$) for Anxiety-only if separated. The lower number of healthy comparisons was included to maximize our ability to detect dimensional effects within patient populations in other planned analyses (in consideration of the total sample size that could be collected).

Table 1. Summary statistics (mean and SD) and group differences for demographic and clinical measures

<u>Full Sample</u>	HCs (N = 59)	DEP/ANX (N = 260)	SUDs (N = 159)	<i>p</i>
Age	32.14 (11.13)	35.89 (11.30)	33.93 (9.09)	0.024
Sex (male)	28 (48%)	70 (27%)	74 (47%)	<0.001
PHQ	0.90 (1.36)	12.63 (5.14)	6.50 (5.66)	<0.001
OASIS	1.27 (1.88)	9.80 (3.42)	5.78 (4.66)	<0.001
DAST-10	0.12 (0.38)	0.67 (1.41)	7.48 (2.20)	<0.001
WRAT	62.37 (5.06)	63.53 (4.76)	58.49 (5.65)	<0.001
<u>Propensity Matched</u>	HCs (N = 59)	DEP/ANX (N = 161)	SUDs (N = 56)	<i>p</i>
Age	32.14 (11.13)	35.11 (10.84)	32.67 (10.26)	0.119
Sex (male)	28 (48%)	41 (25%)	35 (63%)	<0.001
PHQ	0.90 (1.36)	12.64 (5.38)	7.95 (6.50)	<0.001
OASIS	1.27 (1.88)	9.78 (3.42)	6.80 (5.15)	<0.001
DAST-10	0.12 (0.38)	0.62 (1.26)	7.45 (2.65)	<0.001
WRAT	63.53 (4.76)	62.58 (4.53)	61.89 (4.43)	0.15

Data collection procedure

Participants underwent an intensive assessment for demographic, clinical and psychiatric features, with a main focus on negative and positive affect, arousal and cognitive functioning. From this assessment, several direct and derived variables were acquired, only some of which were used in the present analyses. The complete list of assessments and references supporting their validity and reliability are provided in (31).

Approach-avoidance conflict (AAC) task

The AAC task (Figure 1; (11, 30)) is described more extensively in supplementary material. Prior to performing the task, participants received detailed instructions (also provided in supplementary materials) and completed four practice trials to ensure sufficient understanding. On each trial, a runway was shown with a picture of an avatar in a starting position above the runway. Pictures were also shown on each side of the runway, indicating the types of stimuli that could be presented at the end of the trial (see Figure 1). Specifically, a sun or cloud represented potential positive or negative affective stimuli, respectively; while the height of red fill in a rectangle signified the number of points that would be received in conjunction. On each trial, participants could press the left or right arrow keys to move the avatar from its starting position to any other position (9 possible locations) on the runway, and they were asked to choose one ending position on each trial. They were told that each ending position corresponded to a specific probability of observing different stimuli at the end of the trial. These stimuli included a positive

or negative affective image-sound combination (indicated by the sun or cloud, respectively), and a certain level of reward points (indicated by the height of red fill in the rectangle). The ending position of the avatar determined the probability of each of these outcomes occurring. Before starting the task, participants were told the specific probabilities of observing each stimulus for each runway position, and that these probabilities were stable across the task. Thus, there was no learning in this task, and no measure of better/worse performance; participants simply indicated their preferred location on the runway (based on the probabilities of each outcome) on each trial. The probabilities told to the participants were based on the distance from each stimulus (e.g., being closer to the sun image indicated a higher probability of observing the positive stimulus). From left to right on the runway, the probabilities = [.9/.1, .8/.2, .7/.3, .6/.4, .5/.5, .4/.6, .3/.7, .2/.8, .1/.9]. The starting position of the avatar (middle, left end, or right end) was counterbalanced across trials (for each trial type; see below) to control for its potential influence on the participants' choice.

Figure 1. (Left) Example trial in AAC task, in which the negative stimulus and two points were presented based on the probabilities associated with the chosen runway position. (Right) The five trial types. The sun indicates a positive stimulus, the cloud indicates a negative stimulus, and the higher the red bar is filled the more points may be received.

The affective image-sound combinations were gathered from the International Affective Picture System [IAPS] (48), International Affective Digitized Sounds [IADS] (49), and other freely available audio files (see further description in previous reports using this task; (11, 30)). The “reward” included 0, 2, 4, or 6 points presented along with a trumpet sound. There were five trial types (see Figure 1), which were indicated to participants by the images shown on each side of

the runway on each trial. Each trial type was named in reference to the behavioral motivation presumably elicited by the negative/positive affective stimuli and/or the reward points: (1) ‘Avoid-threat’ (AV), in which 0 points were offered for both possible stimulus outcomes and thus, the only explicit motivation was to avoid the negative affective stimulus. (2) ‘Approach-reward’ (APP), in which 2 versus 0 points were offered, each with positive affective stimuli. For this condition, the only explicit motivation was to approach the rewarded outcome. (3)-(5) Three levels of ‘Conflict’ in which the negative affective stimulus was presented in addition to winning either 2 (CONF2), 4 (CONF4), or 6 (CONF6) points, while 0 points were offered for the other possible outcome, in which a positive affective stimulus would be presented. The task consisted of a total of 60 trials, with 12 of each of the five trial types. After task completion, a screen appeared displaying total points received and an award ribbon. As in previous administrations of the task (11, 12), points did not correspond to monetary reward. Notably, previous research has shown that paradigms involving either non-monetary or monetary reward elicit similar neural activation patterns in reward-sensitive brain regions (50, 51), which could suggest similar motivational influences. Behavioral variables consisted of both chosen avatar position and reaction times (RTs; i.e., time to initial button press) during each trial. Participants were asked to fill out a questionnaire that asked about their experience during the task (Table 2).

Table 2. Post-task self-report questionnaire items and Pearson correlations with computational model parameters (full sample; N = 478)

Post-Task Self-Report Questions (Likert Scale: 1 =	Mean	Emotional	Decision
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not at all; 7 = very much)	(SD)	Conflict Parameter (EC)	Uncertainty parameter (β)
1. I found the POSITIVE pictures enjoyable:	5.05 (1.68)	.07	.02
2. The NEGATIVE pictures made me feel anxious Or uncomfortable:	4.43 (1.99)	.32**	.06
3. I often found it difficult to decide which outcome I wanted:	2.51 (1.73)	.10*	.45**
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS:	4.76 (2.30)	-.74**	-.48**
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS:	2.98 (2.17)	.67**	.37**
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture:	5.5 (1.83)	-.37**	-.17**
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself:	2.96 (1.94)	.29**	.11*

8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures	3.26 (1.99)	.32**	.05
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** = $p < .001$; * = $p < .05$

Computational modeling

To model behavior on the AAC task described above, we adopted a Markov decision process (MDP) model under the active inference framework; for more details about the structure and mathematics of this class of models, see (23, 52, 53) and supplementary materials. We chose this model because it is well-suited for modeling decision-making under uncertainty and was designed to model inference and planning processes both with and without learning. This was appropriate here because the AAC task does not involve learning (i.e., participants were explicitly told the probabilities of stimuli/points given each runway position prior to task commencement), which made other common learning-based modelling approaches (e.g., reinforcement learning) inappropriate. This is similar to other previously used behavioral tasks (e.g., the urn or beads task; (54-56)) that rely upon probabilistic inference as opposed to learning – and therefore call for some form of Bayes optimality assumptions (under the complete class theorem; see (56)). Further, as the outcomes of decisions on the AAC task were probabilistic, and participants were explicitly informed about these probabilities when making their choices, a model explicitly incorporating action-outcome probabilities appeared most appropriate for capturing the cognitive processes underlying participants' behavior.

Briefly, this approach requires creating a model with specific sets of observable stimuli (o) and beliefs about states of the task (s), as well as beliefs about the sequences of actions that can be chosen (policies; π). Here, observations included runway position, trial type cues, and positive/negative stimuli + number of points; task states included beliefs about trial type and position on the runway; and policies included transitions to each possible location on the runway. The relationships between these variables at a time (t) are described by a set of matrices. The **A** matrix encodes the way that task states are related to observations, $P(o_t|s_t)$; here, the probability of observing each set of trial type cues given a particular trial type (specified as an identity matrix), the probability of observing the avatar in a given location given a particular runway position (specified as an identity matrix), and the probability of observing different outcome stimuli given each position on the runway (specified based on the stated task probabilities). The **B** matrix encodes the probability that one task state will transition into another depending on selected policies $P(s_{t+1}|s_t, \pi)$; here, this specified that trial type was stable across a trial (identity matrix) and that the participant would deterministically transition from the start state to different runway position states given the selection of different policies. The value of an observation is encoded as a log probability within a matrix referred to as the **C** matrix (implementation in the present model described further below). Policies are selected based on beliefs about the probability that each possible policy will produce preferred observations (i.e., formally, those with the highest prior probability), modulated by an expected precision term (γ) that encodes decision uncertainty. See Table 3 and supplementary materials for further details regarding how observations, states, policies, and associated matrices were defined to model the

AAC task.

Briefly, each trial consisted of two epochs. On the first epoch, the participant was in a “start” state and was presented with the avatar and trial-type cues (observations indicating AV, APP, or CONF2, 4 or 6). Based on the selected policy, on the second epoch the participant then transitioned to the chosen runway position (indicated by movement of the avatar), and observed the outcome stimuli (i.e., image-sound type + number of points), based on the probabilities associated with the chosen runway position. Figure 2 depicts the MDP structure, $\mathbf{A}$ -matrices for the task, and example simulations under different parameter values. Figure 3 provides a visual depiction of the model structure of the AAC task.

Figure 2. Computational Model. (Top Left) Depicts the Markov decision process used to model the approach-avoidance conflict task. The generative model is depicted graphically, such that arrows indicate dependencies between variables. Observations (o) depend on hidden states (s), where this relationship is specified by the **A** matrix, and those states depend on both previous states (as specified by the **B** matrix, or the initial states specified by the **D** matrix) and the sequences of actions/policies (π) selected by the agent. The probability of selecting a particular policy in turn depends on the expected free energy (**G**) of each policy with respect to the prior preferences (**C**) of the agent. The degree to which expected free energy influences policy selection is also modulated by an expected precision term (γ), which is in turn dependent on a prior policy precision parameter (β) – where higher values of β promote greater decision uncertainty (i.e., less influence of the differences in expected free energy across policies). For more details regarding the associated mathematics, see (52, 57) and supplementary materials. In our model, the observations were cues indicating the trial type, cues indicating the position of the avatar, and the outcome stimuli (**A**-Matrices in right panel; columns = start state + runway positions, rows = outcome stimuli, lighter = higher probability). The hidden states included beliefs about trial type and avatar position, and the policies included the choice to move the avatar to any other position on the runway. (Bottom Left) The model parameters corresponded to the degree to which the negative stimulus was dyspreferred relative to the degree to which the points were preferred within the **C** matrix (“emotional conflict”; EC), as well as the prior policy precision parameter β reflecting decision uncertainty. (Top Middle) Example simulations of action selection under different parameter values during the “Conflict + 2 Points” trial type. Blue dots indicate chosen actions and darker colors indicate higher action values in the model (i.e., columns 2-10 correspond to choosing each of the 9 runway positions; right = negative stimulus + 2 points, left = positive stimulus; row 1 and column 1 correspond to the “start” state and associated

observation). Trial Types: AV = Avoid; APP = Approach; CONF2, CONF4, and CONF6 indicate Conflict + 2 Points, 4 Points, or 6 Points, respectively.

Figure 3. Simplified visual depiction of relevant dependencies in the computational (generative) model of the approach-avoidance conflict task. Beliefs about trial type and beliefs about runway positions were generated by (and inferred based on) trial type cues and runway position cues, respectively. Observed outcome stimuli were probabilistically generated by an interaction between trial type and runway position. Beliefs about this interaction were used to infer the action (state transition) most likely to produce the most preferred outcome stimuli. Trial Types: AV = Avoid; APP = Approach; CONF2, CONF4, and CONF6 indicate Conflict + 2 Points, 4 Points, or 6 Points, respectively.

Table 3. Markov decision process model of the AAC task

Model variable	General Definition	Model-specific specification
o_t	Observable outcomes at time t	Outcome modalities:

		<ol style="list-style-type: none"> 1.Observed position on the runway (10 possible observations, including a “starting” position and the nine final positions on the runway that one could choose). 2.Cues indicating trial type (five possible observations, corresponding to the five trial types). 3.Stimuli observed at the end of each trial. This included seven possible observations corresponding to a “starting” observation, the positive stimulus with 0 or 2 points, and the negative affective stimulus with 0, 2, 4, or 6 points.
s_t	Hidden states at time t	<p>Hidden state factors:</p> <ol style="list-style-type: none"> 1.Beliefs about position on the runway (10 possible belief states with an identity mapping to the observations in outcome modality #1). 2.Beliefs about the trial type (corresponding to the five trial types)
π	A distribution over action policies encoding the expectation that a particular policy is being pursued.	Allowable policies included the decision to transition from the starting state to each of the nine possible positions on the runway
β	The prior on expected policy precision term (β) is the 'rate' parameter of a gamma distribution, which is a standard distribution to use as a prior for expected precision (γ). This latter term modulates the influence of expected free energy on policy selection.	When β is high (reflecting low confidence about the best decision), policy selection becomes less deterministic. Higher β values therefore encode participants' decision uncertainty during the task (c.f., the temperature parameter in a conventional softmax response function).
A matrix $P(o_t s_t)$	A matrix encoding beliefs about the relationship between hidden states and observable outcomes (i.e., the likelihood that specific outcomes will be observed given specific hidden states).	Encodes beliefs about the relationship between position on the runway and the probability of observing each outcome, conditional on beliefs about the task condition.

B matrix $P(s_{t+1} s_t)$	A matrix encoding beliefs about how hidden states will evolve over time (transition probabilities).	Encodes beliefs about the way participants could choose to move the avatar, as well as the belief that the task condition will not change within a trial.
C matrix $\ln P(o_t)$	A matrix encoding the degree to which some observed outcomes are preferred over others (technically modeled as prior expectations over outcomes).	Encodes stronger positive preferences for receiving higher amounts of points, and negative preferences for the aversive stimuli (both relative to an anchor value of 0 for the “safe” positive stimulus). The EC parameter in our model encodes the value of participants’ preferences against observing the aversive stimuli.
D matrix $P(s_1)$	A matrix encoding beliefs about (a probability distribution over) initial hidden states.	The simulated agent always begins in an initial starting state, and believes each task condition is stable across each trial.

The **C** matrix was specified such that the expected value assigned to each possible stimulus was determined by three parameters corresponding to the subjective value of observing: the positive affective stimulus, the negative affective stimulus, and each point that could be won. The positive affective stimulus was fixed at an “anchor” value of $\ln P(o) = 0$ and the value of each point was $\ln P(o) = 1$ (i.e., $\ln P(o) = 2$ when winning 2 points, etc.). We then estimated the relative value (subjective aversiveness) of the negative affective stimulus. This parameter indicated the “emotional conflict” (EC) – that is, the expected aversiveness of the affective stimuli relative to the reward value assigned to each point. We also estimated a prior policy precision parameter (β), which is the inverse of the expected precision term γ and acts as an index of an individual’s *a priori* belief-based uncertainty related to making optimal decisions. Higher decision uncertainty in the model (a higher β value) leads to less consistent (more variable) choices over trials, due to less precise beliefs about the best policy (i.e., less confidence

in which action will lead to the most preferred outcomes).

Based on these values, the model infers a probability distribution over possible actions (i.e., transitions to different possible runway positions), and samples actions from this distribution on each trial, where higher action probabilities formally correspond to lower values of a quantity called expected free energy (G ; described more thoroughly in supplementary materials). Briefly, in this context expected free energy scores the (Kullback–Leibler) divergence between distributions reflecting 1) preferred observations (i.e., the combined negative + positive values of images, sounds, and points), and 2) observations expected under each choice of runway position (given knowledge of the associated probabilities). Lower expected free energy of an action thus indicates a higher probability of observing the overall most preferred combination of stimuli/points if that action were chosen.

Our computational phenotyping approach used Bayesian inference at two levels (58). First, each participant's responses were modeled under ideal Bayesian assumptions, using the MDP formulation of choice behavior described previously. Based on the trial-by-trial task stimuli observed by each participant and their trial-by-trial decisions, we then used Variational Bayes to estimate each participant's prior beliefs that maximized the likelihood of their responses, as described in (18). 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 (18, 59). 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 behavioural responses can then be used to assess the likelihood of responses under different prior beliefs. We optimised these preferences (and precision of posterior beliefs about policies) using this likelihood and standard variational Laplace (60). Having estimated each subjects preferences (and precision), we then used classical inference to test for the effects of group, using a standard summary statistic approach.

As described in more detail in supplementary materials, 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 separate terms for the subjective value of the negative affective stimuli and the subjective value of the points (i.e., in place of the EC parameter). Initial simulations indicated that parameter estimates for the 3-parameter model were dependent on prior values (and therefore not recoverable), because 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. However, Bayesian model comparison (based on (61, 62)) showed that this model performed worse than the 2-parameter model (protected exceedance probability = 1).

Analyses

Statistical analyses were conducted using R statistical package (R Core Team, 2018; <https://www.R-project.org/>). To assess face validity, we 1) calculated a model accuracy score reflecting the average percentage of trials during which the action with the highest probability in the model matched the action chosen by participants (i.e., under the parameter values estimated for each participant), and 2) examined correlations between model parameters and RTs (i.e., time to initial button press; both across the whole task and within each condition), with the expectation that valid computational measures of greater emotional conflict (EC) and decision uncertainty (β) would both be associated with slower RTs. We then conducted further correlation analyses to examine whether each parameter could predict subsequent self-reports on the post-task Likert scale questions. The validity of EC would be supported by positive associations with self-reported avoidance motivation and anxiety, and the validity of β would be supported by self-reported difficulty making decisions and self-reported avoidance motivation.

We used the R statistical software package to conduct analyses of covariance (ANCOVAs) to identify possible group differences in each parameter, while accounting for individual differences in age, sex, and the Wide Range Achievement Test reading score (WRAT; a common measure of premorbid IQ (63)), and the interaction between group and each of these factors.

WRAT scores were used to ensure differences in task behavior were not only due to differences in general intelligence. Results were Bonferroni corrected for multiple comparisons with two parameters ($\alpha=0.05$, $p < .025$). To assess group differences in approach/avoidance behavior, we also conducted similar ANCOVAs with the dependent variable being the standard descriptive task variables, including mean chosen runway positions during the AV, APP, and CONF trial

types (higher values indicate stronger approach behavior toward the points; note: in the AV condition, higher values indicate positions closer to the positive stimulus).

As shown in table 1, the groups showed significant differences in age, sex, and WRAT scores, which prevents strong conclusions when trying to control for the effects of these variables (64).

This confirmed group differences anticipated based on the representative demographics within these clinical populations (e.g., see (65-72)). As has been done in previous work on the T1000 dataset (73), to more rigorously assess group differences we therefore used the fullmatch

function within the optmatch¹ R package

(<https://www.rdocumentation.org/packages/optmatch/versions/0.9-10/topics/fullmatch>) to

propensity match groups based on age and WRAT scores (propensity matching was not effective when including sex, given the differences between groups). This led to sample sizes of N = 59 (HCs), N = 161 (DEP/ANX), and N = 56 (SUDs) for the matched sample. We then performed the same analyses described above with the propensity matched groups, with sex and the group by sex interaction as independent variables in the model.

It is important to highlight here that the T1000 study, of which the AAC task analyzed here is a part, was designed explicitly within an exploratory/confirmatory framework, with the first 500 participants designated as exploratory and the second 500 participants reserved for confirmatory analyses based on the exploratory results in the first 500. As such, the analyses reported here should be considered exploratory. Confirmatory analyses will be carried out in planned future work.

¹ This package was originally developed by researchers at the Laureate Institute for Brain Research.

Results

Descriptive statistics for demographic and clinical measures are shown in Table 1. The descriptive statistics for each of the parameters were as follows: β , mean = 4.77 (SD = 4.69); EC, mean = 2.70 (SD = 2.72). For further information about the relationship between model parameters and demographic variables, see supplementary materials. The EC and β parameters were correlated at $r = .26$, $p < .001$. Because the parameters were not normally distributed, they were log-transformed for all subsequent analyses using the R package `optLog` (<https://github.com/kforthman/optLog>) to find the optimal log transform that minimizes skew. Parameter distributions before and after transformation are shown in supplementary materials.

Face validity: Task-related self-report and behavior Averaging across participants, the model was accurate at predicting behavior in 72% (SE = 1%) of trials (note: chance accuracy is $1/9 = 11\%$). Individuals with longer RTs across all trials also exhibited greater EC ($r = .24$, $p < .001$) and higher β values ($r = .59$, $p < .001$). Analyses of RTs within specific trial types showed similar results (supplementary materials). Relationships between model parameters and self-reports on the post-AAC questionnaire items are shown in Table 2. Notably, EC correlated most strongly with self-reported motivations to move towards reward and motivations to move away from negative outcomes. Higher EC also corresponded to higher self-reported anxiety during the task. β correlated most strongly with self-reported difficulty making decisions on the task and (reduced) motivations to move towards reward.

Clinical validity: Diagnostic effects

Here we present group difference results for the propensity matched sample (see figure 4). For analogous results in the full sample, see supplementary materials. Results in the full sample showed a highly similar pattern, as we note more specifically below.

There was a main effect of group on β ($F(2,270) = 4.15, p = .017$), reflecting lower values in HCs than in both DEP/ANX ($t(128) = 2.16, p = .03, d = .30$) and SUDs ($t(102) = 2.88, p = .005, d = .53$); effects of sex and the group by sex interaction were non-significant. A similar pattern was observed in the full sample (supplementary materials).

There was a main effect of sex on EC ($F(1,270) = 11.17, p < .001$; higher in females); effects of group and the group by sex interaction were non-significant. However, there was a trend effect of group in the full sample ($F(2,466) = 3.30, p = .04$), reflecting greater EC in HCs than in SUDs ($t(92) = 3.17, p = .002, d = 0.51$; see supplementary materials for full results).

In supplementary materials, we also present these analyses separately in males and females, and note that the pattern of findings in the EC parameter only remained significant in females, while the pattern of findings in the β parameter only remained significant in males.

Figure 4. Raincloud plots (distributions, boxplots, and individual data points) and bar plots (means and SEs) showing differences between HCs and clinical groups in Emotional Conflict (EC; expected aversiveness of negative stimuli relative to reward) and decision uncertainty (β ; expected policy precision) within the active inference model of the AAC task within the propensity matched sample (left) and the full sample (right). Data displayed is prior to being log-transformed.

Standard descriptive analyses

Descriptive statistics for task-related self-report and traditional performance variables (RT, approach behavior) are provided in supplementary materials. Average RTs across trial types were not significantly different between groups; there was no effect of sex or sex by group interaction. However, in supplementary materials we present some significant group differences

within specific trial types, reflecting slower RTs in the clinical groups relative to HCs. . Similar results were observed in the full sample (supplementary materials).

Within conflict (CONF2, CONF4, CONF6) trials, we observed a main effect of sex on chosen runway position ($F(1, 270) = 7.53, p = .006$; less avoidance in males). Within AV trials, we observed a main effect of sex ($F(1,270) = 5.29, p = .02$; less avoidance of the negative image in males) and group ($F(2,270) = 13.36, p < .001$) on chosen runway position. Further inspection indicated that HCs showed greater avoidance of the negative image in this condition than both the DEP/ANX ($t(177) = 2.42, p = .016, d = .29$) and SUD ($t(72) = 4.90, p < .001, d = .93$) groups. SUDs also showed less avoidance than the DEP/ANX group ($t(75) = 3.59, p < .001, d = .65$). Within APP trials, we observed a main effect of group on chosen runway position ($F(2,270) = 5.04, p = .007$), reflecting greater approach behavior (i.e., toward the points) in HCs than in both DEP/ANX ($t(203) = 3.41, p < .001, d = .38$) and SUDs ($t(81) = 3.67, p < .001, d = .69$). Somewhat similar results were found in the full sample (see supplementary results).

Although not analyzed in previous studies of this AAC task, our decision uncertainty results suggested the presence of differences in within-subject decision variability. See supplementary materials for additional analyses that confirm these differences (most strongly in the AV, APP, and CONF6 trial types) and also show the expected positive correlations between within-subject variability and β values across all trial types.

Discussion

Using a novel active inference modeling approach in a large community sample, this study uncovered separable influences of two factors on approach-avoidance behavior: 1) expected outcome aversiveness relative to expected reward (EC) and 2) decision uncertainty (β). The model showed high accuracy in predicting behavior (72%; i.e., relative to chance accuracy = 11%) and was further validated by the fact that parameter estimates 1) showed strong relationships with RTs and participants' self-reported feelings/motivations during the task, and 2) were strongly correlated with self-reported approach/avoidance motivations, all in the expected directions. Further, EC was uniquely associated with self-reported anxiety on the task, while β was uniquely associated self-reported difficulty making decisions on the task. Crucially, EC and β were not highly correlated, with distinct relationships to psychopathology.

The computational approach used here may provide advantages over previous descriptive analyses of task behavior, as it can disentangle the effects of conflict and uncertainty (11, 30). While previous analyses have focused mainly on relative approach-avoidance drives (i.e., captured by chosen runway position) and RTs, our approach uncovered a unique pattern of differences in decision uncertainty that may have been missed in previous studies. Specifically, our results showed that patients with depression, anxiety, and SUDs exhibited greater uncertainty in decision-making relative to HCs, whereas SUDs tended toward *lower* EC (although this latter finding was marginal). Standard descriptive analyses of RTs and chosen runway position did not pick up on this difference, and, contrary to expectation, did not show evidence of greater avoidance in the clinical groups. Instead, the clinical groups showed no behavioral differences on conflict trials and showed less of the expected approach and avoidance drives in the two non-

conflict conditions. Post-hoc analyses of within-subject choice variability that were motivated by our decision uncertainty results (i.e., which has not been examined in previous studies) also showed greater choice variability in the clinical groups in these non-conflict conditions (as well as in the Conf6 condition; see supplementary materials) – suggesting that a mix of separable approach and avoidance drive abnormalities may contribute to maladaptive behavior during AAC. Thus, our model-based findings uncovered a pattern of decision-uncertainty that might be more clinically relevant to avoidance behavior in real-world settings.

The finding that both clinical groups showed greater β values relative to HCs suggests reduced confidence in their internal model of how to act, and a resulting inconsistency in choice behavior. This is because, formally, the β parameter in active inference models reflects prior expectations about one's ability to select the best action. This is consistent with the correlation we observed between slower RTs and higher β values. Thus, at least in some situations, maladaptive approach-avoidance behavior in SUDs and DEP/ANX could potentially relate more to decision uncertainty than to increased threat sensitivity *per se*. It is also worth noting that our supplementary analyses suggested this effect was stronger in males, which could relate to previous work suggesting that higher anxiety sensitivity more strongly drives avoidance behavior in males than females (12) – which could have important treatment implications (e.g., that different interventions may be necessary in males and females).

It is useful to consider whether current or novel interventions aimed at modifying decision uncertainty may have potential for improving mental health. While many current interventions

for DEP/ANX focus on either threat (i.e., exposure-based therapy) or reward reactivity (i.e., behavioral activation approaches), it is possible that these or other treatment strategies (e.g., cognitive restructuring or problem-solving) may in fact target decision uncertainty.

Investigations concerning relationships between decision uncertainty and response to these treatments would be important for further delineating clinical implications. However, the source of greater uncertainty in the clinical groups is unclear. Based on previous work (41), one possibility could be that psychopathology involves a difficulty separating ‘signal from noise’ when observing the outcomes of actions (i.e., did the outcome of my previous action come about by chance or would the same outcome happen again?). However, this (among other possible interpretations) will need to be tested in future work.

Contrary to our initial hypothesis, the model did not offer evidence that the clinical groups had higher EC. In contrast, we found suggestive evidence for lower EC in SUDs than HCs. Because this finding was only found in the full sample, we do not offer strong interpretations here.

However, we briefly note that this may be consistent with previous studies suggesting a general blunting of brain and behavioral responses to affective stimuli in individuals with cocaine and methamphetamine use disorders (74, 75), and studies that have linked lower self-reported sensitivity to punishment with both methamphetamine and marijuana use (76, 77) – which could relate to continued drug use due to an insensitivity to its negative consequences. This could also potentially relate to previous work demonstrating that cognitive bias modification methods that train increased avoidance in response to alcohol cues is beneficial to recovery in an inpatient alcoholic sample (78). Interestingly, our supplementary analyses suggested this result was

stronger in females, which bears some similarity to previous results suggesting that reduced reward motivation plays a larger role in avoidance behavior females (12).

Our results may also have implications for the active inference literature. For example, previous proposals have suggested a link between state anxiety and the β parameter (79-85) – where higher β is suggested to underpin higher anxiety. However, higher EC, but not higher β , was associated with higher self-reported anxiety during the task (on the post-task Likert scale questionnaire). Our results therefore link state anxiety to the preference distribution in the model – suggesting some individuals with strong anxiety responses may have found the stimuli quite aversive – and yet were highly confident and consistent in their avoidant strategy. Future empirical work in active inference research should therefore disentangle the circumstances in which negative affect is associated with uncertainty vs. avoidance drives in these models. A second implication for active inference stems from previous work linking fluctuations (updates) in β values to phasic dopamine responses (86-89). As substance use has been linked to dopaminergic system dysfunction (e.g., (90, 91)), this model/task could be used during neuroimaging to simulate predicted individual differences in dopaminergic dynamics (associated with differences in β ; (92)) – and perhaps shed further light on the potential role of dopamine and its relation to decision uncertainty in contributing to symptoms and/or treatment response (e.g., the potential role of dopaminergic medications in altering decision uncertainty).

Limitations and Conclusions

This is the first study integrating an active inference model with an affect-based AAC paradigm

in a large, transdiagnostic community-based clinical sample. While the validity of model parameters was supported by the model's high accuracy in predicting behavior, and by the parameters' expected relationships to standard task measures, there are important limitations to consider. As is inevitable when performing model-based analyses, we were required to make certain choices about fixed parameter values. We also chose to use a Bayesian modeling approach, due to the probabilistic nature of the AAC task, but other modeling approaches could have been considered. However, our model comparison results and the correlations observed between model parameters and other self-report/behavioral measures suggest these choices were reasonable. Second, the AAC task used in this study was not designed in advance with modeling explicitly in mind. Future work should investigate potential task modifications that could further disentangle distinct computational influences on approach-avoidance behavior. As this study was exploratory, our results will also need to be replicated by other researchers, as well as in our planned confirmatory analyses on participants sampled from the second 500 participants of the T1000 dataset.

With these limitations in mind, our results demonstrate a novel method of modeling affect-based AAC behavior that was able to differentiate distinct components of conflict. Results demonstrate that, relative to HCs, transdiagnostic behavioral differences during AAC were better accounted for by greater decision uncertainty, as opposed to greater sensitivity to affective stimuli. Future research should replicate these findings and further investigate their potential clinical relevance.

Software Note: All model simulations were implemented using standard routines (here `spm_MDP_VB_X.m`) that are available as Matlab code in the latest version of SPM

academic software: <http://www.fil.ion.ucl.ac.uk/spm/>. Matlab code specifying the generative model of the AAC task is included here in the supplementary material (**AAC_model.m**).

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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, $P(s_{t=1})$.

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**:

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

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

Please note that when the dot ($\cdot$) 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 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 $\mathbf{C}$ matrix). Posterior policy probabilities can be inferred based on the following equation:

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

Where F and G refer to the free energy and expected free energy of a policy, respectively. F is a measure of the perceptual evidence that beliefs about states provide for each policy, and G is a measure of the divergence between actual and preferred observations that also takes into account perceptual uncertainty (or ambiguity):

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

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

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 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):

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

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+2 points, negative affective stimulus+4 points, negative affective stimulus+6 points. Thus, this matrix says that 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 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:

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

From left to right, this assigns value to observing 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]', 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.²

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

² 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.

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 $\beta = 1$. Setting prior values in such models can be somewhat (unavoidably) arbitrary. However, our decision for selecting these priors was 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 $(-1/2)$ 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). $\beta = 1$ 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:

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

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 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 did appear recoverable for the 2-parameter model, and this model was therefore selected for our further analyses.

Supplementary Results

Relationship between model parameters and demographic variables

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 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 S3) 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 SUD ($t(336) = 2.78, p = .006$). 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 ($F(2,297) = 0.21, p = .81$).

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 full sample

During AV trials, there was a main effect of age ($F(1,466) = 12.64, p < .001$; less avoidance of the negative image 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 image 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 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).

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 S4).

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

<u>Question</u>	HCS (N = 59)	DEP/ANX(N = 260)	SUDs (N = 159)	p value*
Full Sample				
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	4.39 (1.83)	4.66 (1.98)	4.08 (2.01)	0.07

uncomfortable:				
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 displayed, I kept my eyes open and looked at the picture:	5.56 (1.87)	5.22 (1.94)**	5.92 (1.55)**	0.03**
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	3.24 (1.82)	3.49 (2.03)	2.89 (1.94)	0.21

strategies to manage emotions triggered by the pictures				
<u>Propensity Matched</u>	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 wanted:	2.05 (1.59)	2.52 (1.77)	2.77 (1.80)	0.08
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	5.56 (1.87)	5.23 (1.96)	6.04 (1.48)	0.28

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)	3.11 (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 pictures	3.24 (1.82)	3.58 (2.07)	2.62 (1.79)	0.07

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

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

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

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

<u>Full Sample</u>	HCS (N = 59)	DEP/ANX(N = 260)	SUDs (N = 159)	p values*
<u>Average reaction time (overall)</u>	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
<u>Propensity Matched</u>	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
Average reaction time	1.14 (0.26)	1.25 (0.33)	1.31 (0.40)	0.017**

(avoid condition)				
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 ANOVAs 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 ANOVAs including Sex and Sex by group interactions.

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

Mean Chosen Runway Position by Trial Type [†] <u>Full Sample</u>	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
<u>Propensity Matched</u>	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
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 ANOVAs 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 ANOVAs including Sex and Sex by group interactions.

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

Standard Deviation in Chosen Runway Position by Trial Type <u>Full Sample</u>	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**
<u>Propensity Matched</u>	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 ANOVAs 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 ANOVAs including Sex and Sex by group interactions.

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

Figure S2. Pearson correlations between model parameter estimates and task reaction times (per task condition).

Figure S3. Differences between HCs and clinical groups (mean and SE) in Emotional Conflict (EC; expected aversiveness of negative stimuli relative to reward) and decision uncertainty (β ; expected policy precision) within the active inference model of the AAC task within the full sample.

**Correlations between decision uncertainty
and within-subject choice variability (SDs)**

	AVOID THREAT	APPROACH REWARD	CONFLICT + 2 POINTS	CONFLICT + 4 POINTS	CONFLICT + 6 POINTS
B (full sample)	0.4	0.64	0.68	0.71	0.7
B (propensity matched)	0.41	0.64	0.68	0.71	0.68

Figure S4. Pearson correlations between decision uncertainty parameter estimates (θ) and within subject choice variability (per task condition).

Matlab code for generative model:

```

% Markov decision process generative model of Approach-Avoidance Conflict Task
% Ryan Smith
clear, close all
%% Specify Parameters
pt_val = 1; %Point value (fixed at 1)
neg_img = 1; %Emotional Conflict
beta = 1; %Decision Uncertainty
%% Specify prior beliefs about initial state: D
%-----
D(1) = [1 0 0 0 0 0 0 0 0 0]'; % positions
D(2) = [1 1 1 1 1]'; % conditions
%% Outcome probabilities: A
%=====
Nf = numel(D);
for f = 1:Nf
    Ns(f) = numel(D(f));
end
No = [7 5 10]; %reward, condition, position
Ng = numel(No);
for g = 1:Ng
    A(g) = zeros([No(g),Ns]);
end
%-----
% states -> stimuli
%avoid threat
A(1) (:,:,1) = [1 0 0 0 0 0 0 0 0 0; % start
               0 9/10 8/10 7/10 6/10 5/10 4/10 3/10 2/10 1/10; % negative image
               0 1/10 2/10 3/10 4/10 5/10 6/10 7/10 8/10 9/10; % positive image
               0 0 0 0 0 0 0 0 0 0; % positive image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +4
               0 0 0 0 0 0 0 0 0 0; % negative image +6
               ];
%approach reward
A(1) (:,:,2) = [1 0 0 0 0 0 0 0 0 0; % start
               0 0 0 0 0 0 0 0 0 0; % negative image
               0 9/10 8/10 7/10 6/10 5/10 4/10 3/10 2/10 1/10; % positive image
               0 1/10 2/10 3/10 4/10 5/10 6/10 7/10 8/10 9/10; % positive image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +4
               0 0 0 0 0 0 0 0 0 0; % negative image +6
               ];
%conflict: 2 points
A(1) (:,:,3) = [1 0 0 0 0 0 0 0 0 0; % start
               0 0 0 0 0 0 0 0 0 0; % negative image
               0 9/10 8/10 7/10 6/10 5/10 4/10 3/10 2/10 1/10; % positive image
               0 0 0 0 0 0 0 0 0 0; % positive image +2
               0 1/10 2/10 3/10 4/10 5/10 6/10 7/10 8/10 9/10; % negative image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +4
               0 0 0 0 0 0 0 0 0 0; % negative image +6
               ];
%conflict: 4 points
A(1) (:,:,4) = [1 0 0 0 0 0 0 0 0 0; % start
               0 0 0 0 0 0 0 0 0 0; % negative image
               0 9/10 8/10 7/10 6/10 5/10 4/10 3/10 2/10 1/10; % positive image
               0 0 0 0 0 0 0 0 0 0; % positive image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +2
               0 1/10 2/10 3/10 4/10 5/10 6/10 7/10 8/10 9/10; % negative image +4
               0 0 0 0 0 0 0 0 0 0; % negative image +6
               ];
%conflict: 6 points
A(1) (:,:,5) = [1 0 0 0 0 0 0 0 0 0; % start
               0 0 0 0 0 0 0 0 0 0; % negative image
               0 9/10 8/10 7/10 6/10 5/10 4/10 3/10 2/10 1/10; % positive image
               0 0 0 0 0 0 0 0 0 0; % positive image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +2
               0 0 0 0 0 0 0 0 0 0; % negative image +4
               0 1/10 2/10 3/10 4/10 5/10 6/10 7/10 8/10 9/10; % negative image +6
               ];
%-----
% states -> trial type (AT, AR, C2, C4, C6)
%avoid threat (AT)
A(2) (:,:,1) = [1 1 1 1 1 1 1 1 1 1; % AT
               0 0 0 0 0 0 0 0 0 0; % AR
               0 0 0 0 0 0 0 0 0 0; % C2
               0 0 0 0 0 0 0 0 0 0; % C4
               0 0 0 0 0 0 0 0 0 0; % C6
               ];
%approach reward (AR)
A(2) (:,:,2) = [0 0 0 0 0 0 0 0 0 0; % AT
               1 1 1 1 1 1 1 1 1 1; % AR
               0 0 0 0 0 0 0 0 0 0; % C2
               0 0 0 0 0 0 0 0 0 0; % C4
               0 0 0 0 0 0 0 0 0 0; % C6
               ];
%conflict: 2 points (C2)
A(2) (:,:,3) = [0 0 0 0 0 0 0 0 0 0; % AT
               0 0 0 0 0 0 0 0 0 0; % AR
               1 1 1 1 1 1 1 1 1 1; % C2
               0 0 0 0 0 0 0 0 0 0; % C4
               0 0 0 0 0 0 0 0 0 0; % C6
               ];
%conflict: 4 points (C4)
A(2) (:,:,4) = [0 0 0 0 0 0 0 0 0 0; % AT
               0 0 0 0 0 0 0 0 0 0; % AR
               0 0 0 0 0 0 0 0 0 0; % C2
               1 1 1 1 1 1 1 1 1 1; % C4
               0 0 0 0 0 0 0 0 0 0; % C6
               ];

```

```

%conflict: 6 points (C6)
A{2}(:, :, 5) = [0 0 0 0 0 0 0 0 0; % AT
                 0 0 0 0 0 0 0 0 0; % AR
                 0 0 0 0 0 0 0 0 0; % C2
                 0 0 0 0 0 0 0 0 0; % C4
                 1 1 1 1 1 1 1 1 1]; % C6

%-----
% states -> runway positions (start,1,2,3,4,5,6,7,8,9)
A{3}(:, :, 1) = eye(Ns(1));
%approach reward
A{3}(:, :, 2) = eye(Ns(1));
%conflict: 2 points
A{3}(:, :, 3) = eye(Ns(1));
%conflict: 4 points
A{3}(:, :, 4) = eye(Ns(1));
%conflict: 6 points
A{3}(:, :, 5) = eye(Ns(1));
%% Controlled transitions: B(u)
%=====
for f = 1:Nf
    B{f} = eye(Ns(f));
end
% controllable transition to any runway position
%-----
for k = 1:Ns(1)
    B{1}(:, :, k) = 0;
    B{1}(k, :, k) = 1;
end
%% allowable policies: V (move to any runway position)
%-----
T = 2;
Np = 9;
V = ones(T-1, Np, Nf);
V(:, :, 1) = [2 3 4 5 6 7 8 9 10];
%% Preference Distribution: C
%-----
C{1} = zeros(No(1), T);
C{2} = zeros(No(2), T);
C{3} = zeros(No(3), T);
C{1}(2, T) = -neg_img;
C{1}(3, T) = 0;
C{1}(4, T) = 2*pt_val;
C{1}(5, T) = -neg_img + 2*pt_val;
C{1}(6, T) = -neg_img + 4*pt_val;
C{1}(7, T) = -neg_img + 6*pt_val;
%% Define MDP Structure
%=====
% Set up MDP
mdp.T = T; % number of moves
mdp.V = V; % allowable policies (deep)
mdp.A = A; % observation model
mdp.B = B; % transition probabilities
mdp.C = C; % preferred outcomes
mdp.D = D; % prior over initial states
mdp.beta = beta;
mdp.alpha = 16;

label.factor{1} = 'Runway Position'; label.name{1} = {'start', '1', '2', '3', '4', '5', '6', '7', '8', '9'};
label.factor{2} = 'Trial Type'; label.name{2} = {'AV', 'APP', 'Conf2', 'Conf4', 'Conf6'};
label.modality{1} = 'Stimuli'; label.outcome{1} = {'Start', 'Neg_stim', 'Pos_stim', 'Pos_stim+2', 'Neg_stim+2', 'Neg_stim+4', 'Neg_stim+6'};
label.modality{2} = 'Trial Type'; label.outcome{2} = {'AV', 'APP', 'Conf2', 'Conf4', 'Conf6'};
label.modality{3} = 'Runway Position'; label.outcome{3} = {'start', '1', '2', '3', '4', '5', '6', '7', '8', '9'};
label.action{1} = {'start', '1', '2', '3', '4', '5', '6', '7', '8', '9'};

mdp.label = label;
mdp = spm_MDP_check(mdp);
MDP = spm_MDP_VB_X(mdp);
spm_figure('GetWin', 'Simulated Behavior'); clf
spm_MDP_VB_trial(MDP);

```