Long-term stability of computational parameters during approach-avoidance conflict in a transdiagnostic psychiatric patient sample

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Abstract

Maladaptive behavior during approach-avoidance conflict (AAC) is common to multiple psychiatric disorders. Using computational modeling, we previously reported that individuals with depression, anxiety, and substance use disorders (DEP/ANX; SUDs) exhibited differences in decision uncertainty and sensitivity to negative outcomes vs. reward (emotional conflict) relative to healthy controls (HCs). However, it remains unknown whether these computational parameters and group differences are stable over time. We analyzed 1-year follow-up data from a subset of the same participants ($N=325$) to assess parameter stability and relationships to other clinical and task measures. We assessed group differences in the entire sample as well as a subset matched for age and IQ across HCs ($N=48$), SUD ($N=29$), and DEP/ANX ($N=121$). We also assessed 2-3 week reliability in a separate sample of 30 HCs. Emotional conflict and decision uncertainty parameters showed moderate 1-year intra-class correlations (.52 and .46) and moderate to excellent correlations over the shorter period (.84 and .54). Similar to previous baseline findings, parameters correlated with multiple response time measures ($ps<.001$) and self-reported anxiety ($r=.30$, $p<.001$) and decision difficulty ($r=.44$, $p<.001$). Linear mixed effects analyses revealed that patients remained higher in decision uncertainty (SUDs, $p = .009$) and lower in emotional conflict (SUDs, $p = .004$, DEP/ANX, $p = .02$) relative to HCs. This computational modelling approach may therefore offer relatively stable markers of transdiagnostic psychopathology.

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

Introduction

Situations eliciting conflict between approach and avoidance drives (approach-avoidance conflict; AAC) are often difficult to handle adaptively for individuals with affective psychopathology ¹. For example, maladaptive avoidance behavior in depression and anxiety disorders (DEP/ANX) can lead individuals to sacrifice participation in rewarding activities due to fear of negative social consequences ². Substance use disorders (SUDs) are also characterized by conflict between strong drug-taking drives and long-term negative outcomes (job loss, loss of close relationships), and decision-making impairments are often observed in substance users on tasks that involve AAC (reviewed in ^{3,4}). The ability to identify stable individual differences in cognition during AAC in these and other clinical populations could be an important step toward the development of individualized treatment selection ⁵.

While there is a growing literature using multiple behavioral tasks to study AAC (⁶⁻¹⁸; for a review, see ¹⁹), this work has not focused on longitudinal aspects of AAC behavior in clinical populations. It is also unclear whether repeated testing of participants with existing behavioral tasks would provide stable individual difference estimates in psychiatric patients. Yet, individual test-retest reliability and stability of group differences are essential components for any paradigm to be used in assessing the effects of treatment (e.g., to assess whether a clinical intervention reduces an objective measure of avoidance behavior). Behavioral paradigms capable of offering stable, clinically relevant measures would therefore be an important advance.

In a recent paper ²⁰, we used a computational modelling approach to analyze behavior on an

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AAC task developed by Aupperle and colleagues ¹¹ in a transdiagnostic sample of patients with DEP/ANX and SUDs. This dataset was part of the Tulsa 1000 (T1000) study ²¹, a naturalistic longitudinal study recruiting subjects based on the dimensional NIMH Research Domain Criteria framework ²². Computational modelling in that study was able to tease apart two components of AAC: decision uncertainty and emotional conflict (aversiveness of negative stimuli relative to reward value). Relative to healthy controls (HCs), we found that all patient groups showed elevated decision uncertainty and also exhibited an unexpected trend toward reduced levels of emotional conflict. Behaviorally, this corresponded to greater choice variability, but less pronounced avoidance on average, in the patient groups. However, the stability of this difference in the patient groups over time, and the ability of the task and modelling approach to capture it, was not addressed.

A central aim in computational psychiatry is to find modeling measures that can be used as either predictors of treatment outcome, to inform personalized medicine approaches, or to track progress in treatment. These aims require that such measures provide reliable estimates of functioning in the domain being assessed. In contrast, if changes with repeated testing reflect random influences, and not change in an underlying mechanism of interest, their use as assessment tools for tracking progress in treatment will be limited. To date there have been relatively few assessments of the test-retest reliability of computational psychiatry measures, with existing studies finding reliability levels ranging from poor to good ²³⁻²⁹. This pattern of results suggests that either the cognitive processes engaged by these tasks differ with repeated performance or that there is significant measurement error. There is thus a need to more fully

assess the longitudinal reliability of available task measures within computational psychiatry research.

In this paper, we perform identical analyses on participants within this sample who performed the AAC task a second time at a 1-year follow-up. We tested the hypothesis that model parameter estimates would show at least fair reliability over the 1-year period (i.e., intra-class correlations greater than .40; criteria for ‘fair’ vs. ‘good’ [greater than .60] reliability are based on ³⁰) and that the same differences between healthy and clinical groups would be found as in the baseline visit. We also explored whether baseline parameter estimates could predict changes in symptoms between baseline and 1-year follow-up. Lastly, we also report test-retest reliability of parameters over a 2-3 week period for a separate sample of 30 healthy control participants.

Method

Participants

Participants for this analysis were identified from the first 500 participants of the Tulsa 1000 (T1000) ²¹, a naturalistic longitudinal study that recruited participants based on the dimensional NIMH Research Domain Criteria framework. The T1000 study had a baseline visit and a 1-year follow up, and 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 ²¹ for a detailed justification based on the aims of the larger study). The participants included in the analyses described here consisted of the subset of participants in our previous study ²⁰ that returned for the 1-year follow-up visit (see below). These participants were

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18-55 years of age, screened on the basis of dimensional psychopathology scores: Patient Health Questionnaire (PHQ ³¹) ≥ 10 , Overall Anxiety Severity and Impairment Scale (OASIS ³²) ≥ 8 , and/or Drug Abuse Screening Test (DAST-10 ³³) 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 ²¹. 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 ³⁴⁻⁴⁴. With the exception of our previous paper ²⁰, none of these papers included analyses using the AAC task. As in our original study ²⁰, 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 (with low to moderate DEP/ANX symptoms; see **Table 1**), and those with DEP/ANX who did not have SUDs. This maintained the transdiagnostic focus while also allowing us to account for potentially distinct effects of substance use. Diagnostic grouping was based on DSM-IV or DSM-5 criteria using the Mini International Neuropsychiatric Inventory (MINI) ⁴⁵ administered at the baseline visit. The DEP/ANX group consisted of individuals with major depression and/or co-morbid anxiety disorders (social anxiety, generalized anxiety, panic,

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and/or posttraumatic stress disorder; baseline: $N=260$, 1-year follow-up: $N=192$), SUDs (recreational drugs excluding alcohol and nicotine, with or without comorbid depression and anxiety disorders; baseline: $N=159$, 1-year follow-up: $N=84$), and HCs with no mental health diagnoses (baseline: $N=59$, 1-year follow-up: $N=49$). In total, 68% of participants completed the follow-up visit (for analyses of potential symptom differences between those that did versus did not complete the follow-up visit, see **Supplementary Materials**).

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

<u>Full Sample</u>	HCs (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)	<i>p</i>
Age	32.71 (11.29)	37.17 (11.42)	36.28 (9.18)	0.039
Sex (male%)	24 (50.0)	50 (26.0)	34 (40.5)	0.002
PHQ Baseline	0.85 (1.27)	12.57 (5.19)	6.88 (6.10)	<0.001
PHQ 1-year follow-up	1.14 (1.84)	8.27 (6.10)	3.10 (4.57)	<0.001
OASIS Baseline	1.38 (2.00)	9.74 (3.47)	5.98 (4.86)	<0.001
OASIS 1-year follow-up	1.47 (2.31)	7.56 (4.58)	3.54 (4.36)	<0.001
DAST-10 Baseline	0.12 (0.39)	0.56 (1.27)	7.46 (2.21)	<0.001
DAST-10 1-year follow-up	0.47 (0.56)	0.56 (1.05)	2.46 (2.89)	<0.001
WRAT Baseline	63.89 (4.54)	63.03 (4.64)	58.49 (6.00)	<0.001
<u>Matched Sample</u>	HCs (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)	<i>p</i>
Age	32.94 (11.29)	36.46 (11.13)	34.06 (9.93)	0.144
Sex (male%)	24 (50.0)	31 (25.6)	13 (44.8)	0.005
PHQ Baseline	0.85 (1.27)	12.57 (5.34)	8.69 (7.49)	<0.001
PHQ 1-year follow-up	1.14 (1.84)	8.10 (6.44)	4.03 (4.12)	<0.001
OASIS Baseline	1.38 (2.00)	9.71 (3.44)	6.93 (5.52)	<0.001
OASIS 1-year follow-up	1.47 (2.31)	7.26 (4.53)	4.52 (4.40)	<0.001
DAST-10 Baseline	0.12 (0.39)	0.53 (1.18)	7.52 (2.69)	<0.001
DAST-10 1-year follow-up	0.47 (0.56)	0.56 (1.18)	2.69 (2.97)	<0.001
WRAT Baseline	63.89 (4.54)	62.88 (4.60)	61.59 (5.34)	0.123

As further described in ²¹, because the T1000 study was built around the NIMH Research Domain Criteria (RDoC) framework that describes dimensions of pathology ²², it 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 found that diagnostic categories offered additional information in our previous study; they also allow more direct connection to previous diagnosis-based studies. The transdiagnostic categories used here (i.e., separating SUDs from DEP/ANX without SUDs) were developed prior to the current analyses and discussed in previous papers ³⁴. Note also that, while the T1000 also included individuals with eating disorders, these were excluded in our original study (and here) due to small sample sizes. Depression and 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 individuals with anxiety disorders without depression. The lower number of HCs 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).

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 ²¹. For this study, we examined the following additional measures that were collected at both baseline and follow-up: the Patient-Reported Outcomes Measurement Information System (PROMIS) depression and anxiety scales ⁴⁶, the Behavioral Activation/Inhibition (BIS/BAS) scales ⁴⁷, the PANAS positive and negative affect scales ⁴⁸, and the anxiety sensitivity index (ASI; ⁴⁹).

Approach-avoidance conflict (AAC) task

The AAC task was described in detail in our previous paper (and elsewhere ^{10,11,20}). For a more detailed description, see **Supplementary Materials**. Briefly, participants were shown an avatar on a runway which could be moved to 9 possible locations, with images of a sun, raincloud, and/or a rectangle with partial red fill on either side (depending on the task condition; see **Figure 1**). They could choose to approach the sun or clouds, where moving closer to one or the other increased the probability of exposure to a pleasant or unpleasant image/sound combination (respectively), with probabilities of $p = .1$ to $.9$ in increments of $.1$ (which was indicated to participants). The higher the red fill on a given side, the more points they could win if they approached that side.

Figure 1. (Left) 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. (Right) 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. This figure is modified from our previous paper²⁰.

There were five trial types: (1) ‘Avoid-threat’ (AV), in which 0 points were offered for both negative and positive stimulus outcomes; (2) ‘Approach-reward’ (APP), in which 2 versus 0 points were offered, each with positive affective stimuli. (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 positive stimulus. The task consisted of a total of 60 trials, with 12 of each of the five trial types. Behavioral variables consisted of both chosen avatar position and response times (RTs; i.e., time to initial button press) during each trial. Participants were also asked to fill out the same post-task Likert scale questionnaire as in our previous study, which asked about their experience during the task (these questions are listed in **Table 4** within the results section).

Computational modeling

To model behavior on the AAC task described above, we used the same Markov decision process (MDP) model as in our previous study; for more details about this class of models, see ⁵¹⁻⁵³. For a detailed description of our model specification, which was identical to our previous study, see **Supplementary Materials**. The model is also described in **Table 2** and illustrated in **Figure 2**. Briefly, the model included observable task stimuli (o ; runway cues, trial type cues, affective stimuli, points), task states (s ; runway position, trial type), and action policies (π ; choice of runway position). Different matrices specified the probability that runway positions would lead to observing different task stimuli, $P(o_t|s_t)$, depending on actions, $P(s_{t+1}|s_t, \pi)$, and the subjective preference for (or aversion to) different task stimuli. An expected precision term (β) encoded decision uncertainty, and an “emotion conflict” (EC) term encoded how subjectively aversive negative stimuli were relative to point values. Higher values for the decision uncertainty term have the effect of increasing the variance of the distribution encoding the probability of selecting one action over others. This means that, all else being equal, individuals that make less

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consistent choices within each trial type will be assigned higher β values (e.g., choosing to approach the negative stimulus sometimes but not others when the same number of points could be won). Higher values for the EC term have the effect of increasing avoidance. This means that, all else being equal, individuals that choose to avoid the negative stimuli when more points could be won will have higher EC values (e.g., only choosing to approach the negative stimuli when 6 points could be won vs. choosing to approach when both 4 or 6 points could be won). For example simulations of behavior under different parameter values, see **Figure S1** in **Supplementary Materials**.

Figure 2. 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. This figure is modified from our previous paper²⁰.

Table 2. 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	Hidden state factors: <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	Allowable policies included the decision to transition from the starting state to each of

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	policy is being pursued.	the nine possible positions on the runway.
β	The prior on expected policy precision (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). The values for each column in this matrix are passed through as softmax function to generate a proper probability distribution, which is then log-transformed.	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.

* Note that t here refers to a participant's beliefs *about* a timepoint in each trial. This means that before a participant makes a choice (i.e., when still in the "start" state), they have prior beliefs about the state at time $t=2$, and these beliefs are then updated after a subsequent observed outcome. In the active inference literature these beliefs *about* timepoints are often instead denoted with the Greek letter tau (τ) in order to distinguish them from the times (t) at which new observations are presented (for details, see ⁵⁴).

All model simulations were implemented using standard routines (here `spm_MDP_VB_X.m`)

that are available as Matlab code in the latest version (Jan 13th, 2020 update) of SPM12 academic

software: <http://www.fil.ion.ucl.ac.uk/spm/>. Matlab code specifying the generative model of the

AAC task is included as an appendix in our original paper ²⁰; additional code used to estimate

parameters is also included as **Supplementary Materials**. As in our previous study, we used Variational Bayes (standard variational Laplace⁵⁵) to estimate model parameters for each participant that maximized the likelihood of each participant's responses, as described in¹⁷; see **Supplementary Materials** for more details. To confirm that parameters were recoverable, we also generated simulated task behavior under 46 representative parameter value combinations present in our participant behavior; we then used Variational Bayes to estimate parameter values from this simulated behavior. Pearson correlations between the true and estimated parameter values were strong (decision uncertainty: $r = .94$; EC: $r = .9$), indicating that model parameters could be accurately estimated.

Analysis of model parameters

Test-retest reliability of individual parameter estimates at baseline and 1-year follow-up was estimated using single-measure consistency intraclass correlations [ICC(3, 1)], which account for fixed effects across time. This ICC measure was chosen due to the expectation that time and/or task familiarity could plausibly influence task behavior across all participants (although we note that the results reported below were nearly identical if assessing agreement instead of consistency). To further assess stability of results over time, we then re-performed the same analyses as in the original paper for the one year follow-up data. Specifically, we first calculated model accuracy metrics, reflecting 1) the average probability of participants' actions under the model and 2) 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). Next, we examined correlations between model

parameters and RTs (i.e., time to initial button press; both across the whole task and within each condition). We also conducted correlation analyses to examine whether each parameter could predict subsequent self-reports on the post-task Likert scale questions.

We then conducted linear mixed effects analyses (LMEs) to confirm the effect of group in each parameter observed in our original study, and to assess potential effects of time (and their interaction). However, in our original study (and as shown in **Table 1**) the groups showed significant differences in age, sex, and Wide Range Achievement Test reading scores (WRAT; a common measure of premorbid IQ⁵⁶), which prevented strong conclusions (i.e., even if controlling for these variables; see⁵⁷ for discussion of limitations in the interpretability of results when controlling for effects of variables for which there are group differences). To more rigorously assess group differences, our previous study used the fullmatch function within the optmatch¹ R package (<https://www.rdocumentation.org/packages/optmatch/versions/0.9-10/topics/fullmatch>; R version 4.0.2) to propensity match groups based on age and WRAT scores (propensity matching was not effective when including sex, given the differences between groups). Here, we similarly performed between-group analyses in the propensity matched groups used at baseline (i.e., the subset of participants in the original groups that returned for the follow-up visit; note that age and WRAT scores remained matched despite dropout, as shown in **Table 1**). Sample sizes for this matched sample (after drop-out between baseline and follow-up) were $N = 48$ (HCs), $N = 121$ (DEP/ANX), and $N = 29$ (SUDs). In **Supplementary Materials**, we present analogous results in the full sample, and we note below whether effects in the matched

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

sample were also present in this larger sample. In these analyses, we expected to again observe greater β values (relative to HCs) in both patient groups at the 1-year follow up, as well as attenuated EC in SUDs. As these were a priori hypotheses focused specifically on confirming our prior results, we did not correct for multiple comparisons.

Excluding HCs, we next tested in exploratory analyses whether baseline parameter estimates could predict changes in clinical presentation between baseline and 1-year follow-up.

Specifically, we used linear regressions to test whether changes in dimensional measures could be predicted (PHQ, OASIS, DAST, PROMIS depression/anxiety, BIS/BAS, PANAS positive/negative affect, ASI), after accounting for scores at baseline as well as age, sex, and WRAT scores. For purposes of hypothesis generation, in **Supplementary Materials** we also describe further exploratory analyses of potential predictive relationships between other task measures and a number of clinical measures available in the T1000 dataset.

Analysis of descriptive task measures

We performed analogous analyses on descriptive task measures, including RTs and mean chosen runway positions. Test-retest reliability of these measures at baseline and 1-year follow-up was estimated using single-measure consistency intraclass correlations [ICC(3, 1)]. To assess group differences, we conducted analogous LMEs with these measures as the dependent variables.

Follow-up analysis of short-term test-retest reliability

To further clarify test-retest reliability for the computational parameters, we estimated model parameters from a second test-retest dataset previously acquired to assess descriptive measures of the AAC task (described in ⁵⁸; also see **Supplementary Materials**). This dataset

included 30 healthy participants (age: mean = 28.9, SD = 8.14; 19 female) who completed the task two times, approximately 2-3 weeks apart. Identical computational and ICC analyses as described above were carried out on this second sample.

Results

Descriptive statistics for demographic and clinical measures are shown in **Table 1**. The descriptive statistics for each of the parameters are shown in **Table 3**. The EC and β parameters were correlated at $r = .19$, $p < .001$. 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.

Table 3. Summary statistics (mean and SD) and group differences for computational measures

Full Sample	HCS (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)
Decision uncertainty (β) Baseline	2.80 (2.56)	4.71 (4.95)	5.01 (4.63)
Decision uncertainty (β) 1- year follow-up	2.33 (2.48)	3.46 (3.92)	4.60 (5.29)
Emotional conflict (EC) Baseline	3.28 (2.76)	3.08 (2.85)	2.06 (2.14)
Emotional conflict (EC) 1- year follow-up	4.47 (3.66)	3.30 (3.42)	1.99 (2.16)
Matched Sample	HCS (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)
Decision uncertainty (β) Baseline	2.80 (2.56)	4.73 (5.22)	4.71 (5.66)
Decision uncertainty (β) 1- year follow-up	2.36 (2.49)	3.35 (4.00)	3.74 (5.03)
Emotional conflict (EC)	3.28 (2.76)	3.23 (3.07)	2.18 (2.39)

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Baseline			
Emotional conflict (EC) 1-year follow-up	4.43 (3.68)	3.27 (3.37)	2.35 (2.75)

Intraclass correlations

Across all participants, the ICC between baseline and 1-year follow-up was fair for both β (ICC = .46; $F(323,323) = 2.68$, $p < .001$) and EC values (ICC = .52 ($F(323,323) = 3.2$, $p < .001$)).

Similar results were found when examining groups separately (see **Supplementary Materials**).

As detailed in **Supplementary Materials**, ICCs across participants, and by group, also showed fair to good reliability in each of the five task conditions for both RTs (ICCs between 0.5 and 0.61) and mean chosen runway position (ICCs between 0.4 and 0.56); with the exception that, in HCs, reliability of mean chosen runway in the AV and APP conditions was poor (ICC = 0.23 and -.03, respectively). ICCs for dimensional clinical measures also showed fair to good reliability over the 1-year period (ICCs between 0.56 and 0.70; with the exception of the DAST, with ICC = .43; see **Supplementary Materials**).

Face validity: Task-related self-report and behavior

Averaging across participants, model accuracy at 1-year follow-up was 81% (SE = 1.3; note: chance accuracy is $1/9 = 11\%$). The average probability of participants' actions under the model was $p = .68$ (SE = .02). Confirming our prior result at baseline, individuals with slower RTs in each trial type exhibited higher β values ($r = .33$ for the AV condition; $r = .55$ -.58 for the other four conditions, $p < .001$ each). Higher EC values were associated with slower RTs in the three

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conflict conditions ($r = .17-.20$, $p < .001$ each) and faster RTs in the AV condition (i.e., individuals with greater sensitivity to the unpleasant stimuli, as indicated by higher EC, responded faster during AV trials; $r = -.28$, $p < .001$).

Table 4 shows the relationships between model parameters and self-report metrics on the post-AAC questionnaire items at 1-year follow-up, and also compares mean scale scores pre-to-post. Notably, all significant correlations found at baseline were replicated at 1-year follow-up. EC again correlated most strongly with self-reported motivations to move toward reward ($r = -0.83$, $p < 0.001$) and away from negative outcomes ($r = 0.75$, $p < 0.001$). Higher EC also corresponded to higher self-reported anxiety during the task ($r = 0.30$, $p < 0.001$); β again correlated most strongly with self-reported difficulty making decisions on the task ($r = 0.44$, $p < 0.001$) and (reduced) motivations to move toward reward ($r = -0.37$, $p < 0.001$).

Table 4. Post-task self-report questionnaire items at baseline and follow-up, and correlations with computational model parameters at follow-up

Post-Task Self-Report Questions (Likert Scale: 1 = not at all; 7 = very much)	Mean (SD) Baseline (N=478)	Mean (SD) 1-Year Follow-up (N=325)	Emotional Conflict Parameter (EC)	Decision Uncertainty parameter (β)
1. I found the POSITIVE pictures enjoyable.	5.04 (1.69)	5.04 (1.54)	.04	-.01
2. The NEGATIVE pictures made me feel anxious Or uncomfortable.	4.43 (1.99)	4.25 (1.96)	.30**	.16*
3. I often found it difficult to decide which outcome I wanted.	2.51 (1.73)††	2.00 (1.57)††	-.08	.44**

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4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS.	4.76 (2.30)	4.83 (2.48)	-.83**	-.37**
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS.	2.98 (2.17)	3.17 (2.39)	.75**	.24**
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture.	5.49 (1.83)†	5.17 (2.02)†	-.47**	-.19**
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)††	3.34 (2.08)††	.28**	.09
8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures.	3.26 (1.99)†	3.61 (2.07)†	.24**	.11*

†† = $p < .01$; † = $p < .05$ (pre-post differences)

** = $p < .01$; * = $p < .05$ (correlations at follow-up)

Clinical validity: Diagnostic effects

Here, we present group difference results for the matched sample (see **Figure 3**). Results in the full sample are provided in **Supplementary Materials**, and showed a highly similar pattern (as we note more specifically below).

An LME revealed main effects of group ($F(2,274) = 3.5, p = .03$) and time ($F(1,230) = 14.1, p < .001$) on β values. Post-hoc contrasts revealed that the group main effect reflected higher values in SUDs than in HCs ($p = .009$, Cohen's $d = .29$) and the time main effect indexed lower values at 1-year follow up than at baseline ($p < .001$); effects of sex, and interactions between group and sex or time were non-significant. A similar pattern was observed in the full sample (see

Supplementary Materials).

There was a main effect of group ($F(2,275) = 4.6, p = .01$) and sex on EC ($F(1,277) = 249.1, p < .001$). Post-hoc contrasts revealed that these effects reflected higher EC in females and greater EC in HCs than in both DEP/ANX ($p = .02, d = .21$) and SUDs ($p = .004, d = .63$). A similar pattern was observed in the full sample (see **Supplementary Materials**); however, in the full sample there was also a group by sex interaction suggesting that group effects were only significant in females.

Figure 3. Means and standard errors for model parameters by clinical group and time in both the propensity matched and full samples. Bar graphs include baseline participant values both with and without follow-up data. Spaghetti plots only include participants with both baseline and follow-up data (thick lines indicate group means, surrounding shading indicates standard error). Comparison of bar graphs and spaghetti plots illustrates that relative differences between groups were somewhat more consistent between baseline and follow-up when including all baseline data.

Clinical Prediction

When accounting for baseline scores, age, sex, and WRAT, exploratory linear regressions (excluding HCs, full sample) revealed a significant relationship between EC at baseline and change in BIS scores from baseline to follow-up ($t(6,242) = 2.03, p = .04$), indicating that higher EC values at baseline predicted larger increases (or smaller decreases) in behavioral inhibition over time. For descriptive statistics and group difference analyses for BIS scores (motivated by these results), see **Supplementary Materials**. No other effects were found supporting the ability of baseline parameter values to predict changes over time in PHQ, OASIS, DAST, BAS, ASI, PROMIS depression/anxiety scales, or PANAS positive and negative affect scales (all $ps > .05$). Additional exploratory analyses also did not find any significant associations between pre-post changes in parameter estimates and pre-post changes in any of these measures.

Descriptive analyses

To help interpret computational modelling results and allow comparability with previous ACC studies, we also performed secondary LMEs on traditional behavioral task variables. These analyses and descriptive statistics for task-related self-report and traditional performance variables (RT, approach behavior) are provided in **Supplementary Materials**. Among other effects, these revealed that RTs were faster in HCs than both clinical groups in the AV condition. HCs showed greater avoidance than the clinical groups for all but the APP trials. Greater within-subject choice variability was seen in SUDs than in the other groups. Both patient groups

reported greater decision difficulty than HCs, and HCs reported less approach motivation and greater avoidance motivation than the patient groups.

Short-term test-retest reliability

Descriptive statistics for behavior in the second sample of healthy participants, with a test-retest interval of approximately 2-3 weeks apart, are shown in **Supplementary Materials**. Analysis of this data showed excellent reliability for the EC parameter ($ICC = .84$ ($F(29, 29) = 11.3$, $p < .001$) and fair reliability for the β parameter ($ICC = .54$; $F(29, 29) = 3.32$, $p < .001$).

Discussion

In this paper, we have demonstrated that a computational modelling approach to studying AAC task behavior is able to capture moderately stable individual differences – and stable psychiatric group differences – over a period of 1 year between a baseline and follow-up visit. Despite the lengthy one year time period between visits, ICCs were moderate. At this 1-year follow-up, relationships between model parameter estimates and task-related RTs, self-reported motivations, and descriptive behavioral measures were consistent with what we previously found at baseline. Of particular interest, greater decision uncertainty (β) in the model remained associated with greater self-reported decision difficulty and slower RTs, while greater emotion conflict (EC) in the model remained associated with greater self-reported anxiety and avoidance motivation. Further, differences between diagnostic groups in model parameters were also stable between baseline and 1-year follow-up. Namely, the SUD group showed greater β values than HCs at both timepoints (with DEP/ANX taking intermediate values between the two), and both

patient groups showed lower EC at both timepoints (see **Figure 3**).

When reliability was assessed in a second healthy sample with a shorter test-retest interval (approximately 2-3 weeks), ICCs were excellent for EC but remained fair for β . This suggests that the lower ICCs for EC over the 1-year period in the main sample may reflect true underlying changes in participants' decision processes (as opposed to measurement error). This parameter therefore shows promise as a repeatable assessment tool at the individual level. In contrast, results for β suggest greater measurement error at the individual level. This may be due in part to task familiarity effects, in which participants become more confident in a decision strategy with repeated task performance (i.e., consistent with the reduced mean and variability in β values at retest in this sample; see **Supplementary Materials**). These findings complement previous work reporting fair to excellent reliability for descriptive behavioral measures and for activation in some brain regions of interest to the same AAC task during functional MRI (e.g., dorsal anterior cingulate during decision-making; amygdala during processing of affective outcomes; ⁵⁸).

Together, these results 1) support the validity of the model/task in being able to provide moderately consistent results with repeated use over a relatively long period of time, and 2) support the ability of model parameters to act as stable markers of clinical group differences. The moderate ICCs suggest relatively consistent individual differences (accounting for the stable group differences) that may have also been influenced by heterogeneous experiences over the 1-year period. However, we were unable to identify other variables that could account for

variability in pre-post changes (e.g., no relationships with symptom changes).

The diagnostic group differences increased confidence in the somewhat unexpected findings in our previous report²⁰. Specifically, the finding that HCs show greater EC values than the patient groups appears reliable. This is consistent with HCs exhibiting greater avoidance during CONF and AV conditions, and greater approach during APP conditions (i.e., in the full sample) in descriptive analyses (see **Supplementary Materials**). It is also consistent with the findings that HCs exhibited faster RTs in the AV condition and greater self-reported avoidance (and reduced approach) motivations during the task (i.e., marginal in the matched sample, but significant in the full sample; see **Supplementary Materials**). In other words, HCs exhibited behavior consistently driven by the potential outcomes in expected directions (e.g., avoiding more in response to negative outcomes; approaching more when there was only reward), whereas the behavior of the DEP/ANX and SUD groups was less expected. This could be related to reduced reward-seeking in depression, which is consistent with our observation that those with lower EC values at baseline tended to have reduced levels of behavioral inhibition (BIS scores) over time. Lower EC (and less avoidance) in patients might also suggest a decreased sensitivity or reactivity to negative stimuli (consistent with a previous body of work in SUDs; see⁵⁹⁻⁶³). One additional possibility is that the patients' experience of greater ambiguity or uncertainty when judging the appropriate response under different conflict conditions may lead them to place the avatar near the middle of the runway rather than fully committing to an approach or avoidance strategy (as HCs tended to do; see histograms within **Supplementary Materials**).

Our results also lend added confidence to our prior result demonstrating greater β values in SUDs. This was part of a larger consistent pattern involving greater self-reported decision difficulty in SUDs (and DEP/ANX) than HCs, and slower RTs in the AV condition (i.e., suggesting less confidence in what choice to make; see **Supplementary Materials**). They also provide added support for the possibility that elevated decision uncertainty during AAC may be an important aspect of psychopathology, which previous behavioral analyses have not distinguished from emotional conflict^{10,64}. Notably, there were stable reductions in β values for all three groups. Due to the generality of this effect across all participants, it is most plausibly an effect of task familiarity at the 1-year follow-up, as participants may have become more confident in their decision strategy (as also mentioned above with respect to the smaller test-retest sample).

Our exploratory finding that EC values at baseline could predict behavioral inhibition at follow-up suggests the possibility that this measure could have predictive clinical utility. However, this will need to be confirmed in an independent sample. Dissapointingly, we did not find evidence that parameter estimates at baseline could predict changes in other dimensional or symptom measures over the following year, suggesting that our paradigm may be better thought of as providing a stable marker of membership to one or more diagnostic categories. However, predictive utility in this sample may have been limited due to the heterogeneity in experiences over the 1-year period (e.g., with some participants seeking various forms of treatment while others did not). It may still be beneficial to determine whether these AAC parameters could be useful for predicting outcomes of specific pharmacological or behavioral treatments targeting

threat or reward responsivity and/or decision-making.

Limitations and Conclusions

While our findings offer strong support for the validity of the model and its ability to provide moderately stable individual difference estimates in clinical populations with repeated testing, it is important to highlight persisting limitations. First, while the group differences were remarkably stable, ICCs were only moderate, and the factors leading to pre-post differences remain to be identified. Results in the small follow-up sample of healthy participants indicated that the EC parameter had excellent reliability when retested after a shorter period of 2-3 weeks, which suggested that changes in this parameter over the 1-year period could reflect genuine changes in underlying decision processes. However, an important question to be addressed in future research is whether ICCs are also higher in patient populations when the task is repeated over shorter intervals of time, and whether larger samples would confirm the effect in healthy subjects. If so, this would provide stronger support for the use of these model parameters as stable individual difference measure, whereas our lengthy 1-year follow-up period may have involved meaningful changes in underlying mechanisms of interest. It is also worth highlighting that ICCs could be limited by parameter estimation itself. Specifically, while simulations indicated strong recoverability, any variability in estimation accuracy between baseline and follow-up would reduce ICCs. Next, while our results replicate previous effects observed in the same sample, they do not replicate our initial results in a new sample of participants. Replication in a new sample will be necessary to support the ability of the task/model to highlight differences

that generalize to broader psychiatric populations. The second 500 participants of the T1000 are set aside specifically for pre-registered replication analyses and we plan to next replicate these results in this confirmatory sample.

Another limitation stems from the fact that 32% of participants did not complete the follow-up visit. We can therefore not rule out that selection effects contributed to our results. While supplementary analyses did not reveal differences in baseline depression/anxiety symptoms between completers and non-completers, those who did not complete the follow-up visit did have higher substance use severity at baseline. A final limitation concerns our inability to match the proportion of males and females across groups, where there were a greater number of females in the DEP/ANX group than the other two groups. As in our previous study on the baseline data, females also had greater EC values. This allows for the possibility that greater EC values in the DEP/ANX group could be explained in part by including a greater number of females. Although not the focus of this study (as this effect was stable over time), this sex difference may relate to other work showing that reduced reward motivation plays a larger role in avoidance behavior in females (12) – raising the possibility that different targets of intervention may be most effective for females vs. males or depending on the relative role of reward and avoidance motivations.

With these limitations in mind, our results demonstrate that AAC behavior shows consistent patterns of individual and group differences over a 1-year period and that the present task and model may act as a stable and reliable marker of these differences over repeated performance – a necessary feature for many practical uses in computational psychiatry. Future research should

replicate these findings in a new sample and further investigate their potential clinical relevance.

Data Availability: The data used in the analyses reported in this study and the code for running the AAC paradigm are available upon request. The Matlab code used to build the task model and estimate parameters is included in **Supplementary Materials**.

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References

- 1 Aupperle, R. & Paulus, M. Neural systems underlying approach and avoidance in anxiety disorders. *Dialogues in clinical neuroscience* **12**, 517 (2010).
- 2 Barlow, D., Allen, L. & Choate, M. Toward a Unified Treatment for Emotional Disorders - Republished Article. *Behavior therapy* **47**, 838-853, doi:10.1016/j.beth.2016.11.005 (2016).
- 3 Ekhtiari, H., Victor, T. A. & Paulus, M. P. Aberrant decision-making and drug addiction—how strong is the evidence? *Current opinion in behavioral sciences* **13**, 25-33 (2017).
- 4 Guttman, Z., Moeller, S. J. & London, E. D. Neural underpinnings of maladaptive decision-making in addictions. *Pharmacology, biochemistry, and behavior* **164**, 84-98 (2018).
- 5 Paulus, M. P. Evidence-Based Pragmatic Psychiatry-A Call to Action. *JAMA Psychiatry* **74**, 1185-1186, doi:10.1001/jamapsychiatry.2017.2439 (2017).
- 6 Lejuez, C. *et al.* Evaluation of a behavioral measure of risk taking: the Balloon Analogue Risk Task (BART). *Journal of experimental psychology. Applied* **8**, 75-84, doi:10.1037//1076-898X.8.2.75 (2002).
- 7 Bechara, A., Damasio, H., Tranel, D. & Damasio, A. Deciding advantageously before knowing the advantageous strategy. *Science* **275**, 1293-1295 (1997).
- 8 Talmi, D., Dayan, P., Kiebel, S. J., Frith, C. D. & Dolan, R. J. How humans integrate the prospects of pain and reward during choice. *J Neurosci* **29**, 14617-14626, doi:10.1523/JNEUROSCI.2026-09.2009 (2009).

- 9 Schlund, M. W. *et al.* The tipping point: Value differences and parallel dorsal-ventral frontal circuits gating human approach-avoidance behavior. *Neuroimage* **136**, 94-105, doi:10.1016/j.neuroimage.2016.04.070 (2016).
- 10 Aupperle, R. L., Melrose, A. J., Francisco, A., Paulus, M. P. & Stein, M. B. Neural substrates of approach-avoidance conflict decision-making. *Hum Brain Mapp* **36**, 449-462, doi:10.1002/hbm.22639 (2015).
- 11 Aupperle, R. L., Sullivan, S., Melrose, A. J., Paulus, M. P. & Stein, M. B. A reverse translational approach to quantify approach-avoidance conflict in humans. *Behav Brain Res* **225**, 455-463, doi:10.1016/j.bbr.2011.08.003 (2011).
- 12 Rinck, M. & Becker, E. S. Approach and avoidance in fear of spiders. *J Behav Ther Exp Psychiatry* **38**, 105-120, doi:10.1016/j.jbtep.2006.10.001 (2007).
- 13 Friston, K., Stephan, K., Montague, R. & Dolan, R. Computational psychiatry: the brain as a phantastic organ. *The lancet. Psychiatry* **1**, 148-158, doi:10.1016/S2215-0366(14)70275-5 (2014).
- 14 Huys, Q., Maia, T. & Frank, M. Computational psychiatry as a bridge from neuroscience to clinical applications. *Nature Neuroscience* **19**, 404-413, doi:10.1038/nn.4238 (2016).
- 15 Montague, P., Dolan, R., Friston, K. & Dayan, P. Computational psychiatry. *Trends in Cognitive Sciences* **16**, 72-80, doi:10.1016/j.tics.2011.11.018 (2012).
- 16 Petzschner, F., Weber, L., Gard, T. & Stephan, K. Computational Psychosomatics and Computational Psychiatry: Toward a Joint Framework for Differential Diagnosis. *Biological Psychiatry* **82**, 421-430, doi:10.1016/j.biopsych.2017.05.012 (2017).
- 17 Schwartenbeck, P. & Friston, K. J. Computational Phenotyping in Psychiatry: A Worked Example. *eNeuro* **3**, ENEURO.0049-0016.2016, doi:10.1523/ENEURO.0049-16.2016 (2016).
- 18 Krypotos, A. M., Beckers, T., Kindt, M. & Wagenmakers, E. J. A Bayesian hierarchical diffusion model decomposition of performance in Approach-Avoidance Tasks. *Cogn Emot* **29**, 1424-1444, doi:10.1080/02699931.2014.985635 (2015).
- 19 Kirlic, N., Young, J. & Aupperle, R. L. Animal to human translational paradigms relevant for approach avoidance conflict decision making. *Behav Res Ther* **96**, 14-29, doi:10.1016/j.brat.2017.04.010 (2017).
- 20 Smith, R. *et al.* Greater decision uncertainty characterizes a transdiagnostic patient sample during approach-avoidance conflict: a computational modeling approach. *Journal of Psychiatry & Neuroscience* **46**, E74-E87, doi:10.1503/jpn.200032 (2021).
- 21 Victor, T. A. *et al.* Tulsa 1000: a naturalistic study protocol for multilevel assessment and outcome prediction in a large psychiatric sample. *BMJ Open* **8**, e016620, doi:10.1136/bmjopen-2017-016620 (2018).
- 22 Insel, T. *et al.* Research domain criteria (RDoC): toward a new classification framework for research on mental disorders. *The American journal of psychiatry* **167**, 748-751, doi:10.1176/appi.ajp.2010.09091379 (2010).
- 23 Hedge, C., Bompas, A. & Sumner, P. Task Reliability Considerations in Computational Psychiatry. *Biol Psychiatry Cogn Neurosci Neuroimaging* **5**, 837-839, doi:10.1016/j.bpsc.2020.05.004 (2020).

- 24 Brown, V. M., Chen, J., Gillan, C. M. & Price, R. B. Improving the Reliability of Computational Analyses: Model-Based Planning and Its Relationship With Compulsivity. *Biol Psychiatry Cogn Neurosci Neuroimaging* **5**, 601-609, doi:10.1016/j.bpsc.2019.12.019 (2020).
- 25 Shahar, N. *et al.* Improving the reliability of model-based decision-making estimates in the two-stage decision task with reaction-times and drift-diffusion modeling. *PLoS Comput Biol* **15**, e1006803, doi:10.1371/journal.pcbi.1006803 (2019).
- 26 Price, R. B., Brown, V. & Siegle, G. J. Computational Modeling Applied to the Dot-Probe Task Yields Improved Reliability and Mechanistic Insights. *Biol Psychiatry* **85**, 606-612, doi:10.1016/j.biopsych.2018.09.022 (2019).
- 27 Enkavi, A. Z. *et al.* Large-scale analysis of test-retest reliabilities of self-regulation measures. *Proc Natl Acad Sci U S A* **116**, 5472-5477, doi:10.1073/pnas.1818430116 (2019).
- 28 Moutoussis, M. *et al.* Change, stability, and instability in the Pavlovian guidance of behaviour from adolescence to young adulthood. *PLoS Comput Biol* **14**, e1006679, doi:10.1371/journal.pcbi.1006679 (2018).
- 29 Chung, D. *et al.* Valuation in major depression is intact and stable in a non-learning environment. *Sci Rep* **7**, 44374, doi:10.1038/srep44374 (2017).
- 30 Cicchetti, D. V. Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. *Psychological Assessment* **6**, 284–290 (1994).
- 31 Kroenke, K., Spitzer, R. L. & Williams, J. B. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med* **16**, 606-613, doi:10.1046/j.1525-1497.2001.016009606.x (2001).
- 32 Norman, S. B., Hami Cissell, S., Means-Christensen, A. J. & Stein, M. B. Development and validation of an overall anxiety severity and impairment scale (OASIS). *Depression and Anxiety* **23**, 245-249 (2006).
- 33 Bohn, M., Babor, T. & Kranzler, H. Validity of the Drug Abuse Screening Test (DAST-10) in inpatient substance abusers. *Problems of drug dependence* **119**, 233-235 (1991).
- 34 Aupperle, R. L. *et al.* Web-Based Graphic Representation of the Life Course of Mental Health: Cross-Sectional Study Across the Spectrum of Mood, Anxiety, Eating, and Substance Use Disorders. *JMIR Ment Health* **7**, e16919, doi:10.2196/16919 (2020).
- 35 Misaki, M. *et al.* Connectome-wide search for functional connectivity locus associated with pathological rumination as a target for real-time fMRI neurofeedback intervention. *Neuroimage Clin* **26**, 102244, doi:10.1016/j.nicl.2020.102244 (2020).
- 36 Ekhtiari, H., Kuplicki, R., Yeh, H. W. & Paulus, M. P. Physical characteristics not psychological state or trait characteristics predict motion during resting state fMRI. *Sci Rep* **9**, 419, doi:10.1038/s41598-018-36699-0 (2019).
- 37 Stewart, J. L. *et al.* Interoceptive attention in opioid and stimulant use disorder. *Addict Biol*, e12831, doi:10.1111/adb.12831 (2019).

- 38 Feng, C. *et al.* Neighborhood affluence is not associated with positive and negative valence processing in adults with mood and anxiety disorders: A Bayesian inference approach. *Neuroimage Clin* **22**, 101738, doi:10.1016/j.nicl.2019.101738 (2019).
- 39 Le, T. T. *et al.* A Nonlinear Simulation Framework Supports Adjusting for Age When Analyzing BrainAGE. *Front Aging Neurosci* **10**, 317, doi:10.3389/fnagi.2018.00317 (2018).
- 40 Huang, H., Thompson, W. & Paulus, M. P. Computational dysfunctions in anxiety: Failure to differentiate signal from noise. *Biological psychiatry* **82**, 440-446 (2017).
- 41 Ford, B. N. *et al.* Association of Early-Life Stress With Cytomegalovirus Infection in Adults With Major Depressive Disorder. *JAMA Psychiatry* **76**, 545-547, doi:10.1001/jamapsychiatry.2018.4543 (2019).
- 42 Clausen, A. N. *et al.* Machine Learning Analysis of the Relationships Between Gray Matter Volume and Childhood Trauma in a Transdiagnostic Community-Based Sample. *Biol Psychiatry Cogn Neurosci Neuroimaging* **4**, 734-742, doi:10.1016/j.bpsc.2019.03.001 (2019).
- 43 Al Zoubi, O. *et al.* EEG Microstates Temporal Dynamics Differentiate Individuals with Mood and Anxiety Disorders From Healthy Subjects. *Front Hum Neurosci* **13**, 56, doi:10.3389/fnhum.2019.00056 (2019).
- 44 Al Zoubi, O. *et al.* Predicting Age From Brain EEG Signals-A Machine Learning Approach. *Front Aging Neurosci* **10**, 184, doi:10.3389/fnagi.2018.00184 (2018).
- 45 Sheehan, D. V. *et al.* The Mini-International Neuropsychiatric Interview (M.I.N.I.): the development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. *The Journal of Clinical Psychiatry* **59 Suppl 20**, 22-33;quiz 34-57 (1998).
- 46 Cella, D. *et al.* The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005–2008. *Journal of clinical epidemiology* **63**, 1179-1194 (2010).
- 47 Carver, C. S. & White, T. L. Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. *Journal of personality and social psychology* **67**, 319 (1994).
- 48 Watson, D., Clark, L. A. & Tellegen, A. Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology* **54**, 1063-1070, doi:10.1037//0022-3514.54.6.1063 (1988).
- 49 Sandin, B., Chorot, P. & McNally, R. J. Anxiety sensitivity index: normative data and its differentiation from trait anxiety. *Behav Res Ther* **39**, 213-219 (2001).
- 50 Lang, P., Bradley, M. & Cuthbert, B. International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8. (2008).
- 51 Friston, K. J., FitzGerald, T., Rigoli, F., Schwartenbeck, P. & Pezzulo, G. Active Inference: A Process Theory. *Neural Computation* **29**, 1-49, doi:10.1162/NECO_a_00912 (2017).
- 52 Friston, K. J., Parr, T. & de Vries, B. The graphical brain: Belief propagation and active inference. *Network Neuroscience* **1**, 381-414, doi:10.1162/NETN_a_00018 (2017).

- 53 Parr, T. & Friston, K. J. Working memory, attention, and salience in active inference. *Scientific Reports* **7**, 14678, doi:10.1038/s41598-017-15249-0 (2017).
- 54 Smith, R., Friston, K. & Whyte, C. A Step-by-Step Tutorial on Active Inference and its Application to Empirical Data. *PsyArXiv*, <https://doi.org/10.31234/osf.io/b31234jm31236> (2021).
- 55 Friston, K., Mattout, J., Trujillo-Barreto, N., Ashburner, J. & Penny, W. Variational free energy and the Laplace approximation. *Neuroimage* **34**, 220-234, doi:10.1016/j.neuroimage.2006.08.035 (2007).
- 56 Johnstone, B., Callahan, C. D., Kapila, C. J. & Bouman, D. E. The comparability of the WRAT-R reading test and NAART as estimates of premorbid intelligence in neurologically impaired patients. *Arch Clin Neuropsychol* **11**, 513-519 (1996).
- 57 Miller, G. A. & Chapman, J. P. Misunderstanding analysis of covariance. *J Abnorm Psychol* **110**, 40-48, doi:10.1037//0021-843x.110.1.40 (2001).
- 58 McDermott, T. J. *et al.* Test-retest reliability of approach-avoidance conflict decision making during functional magnetic resonance imaging in healthy adults. *Hum Brain Mapp* **In Press** (2021).
- 59 Stewart, J. L. *et al.* You are the danger: attenuated insula response in methamphetamine users during aversive interoceptive decision-making. *Drug Alcohol Depend* **142**, 110-119, doi:10.1016/j.drugalcdep.2014.06.003 (2014).
- 60 Hester, R., Bell, R. P., Foxe, J. J. & Garavan, H. The influence of monetary punishment on cognitive control in abstinent cocaine-users. *Drug Alcohol Depend* **133**, 86-93, doi:10.1016/j.drugalcdep.2013.05.027 (2013).
- 61 Simons, J. S., Dvorak, R. D. & Batien, B. D. Methamphetamine use in a rural college population: associations with marijuana use, sensitivity to punishment, and sensitivity to reward. *Psychol Addict Behav* **22**, 444-449, doi:10.1037/0893-164X.22.3.444 (2008).
- 62 Simons, J. S. & Arens, A. M. Moderating effects of sensitivity to punishment and sensitivity to reward on associations between marijuana effect expectancies and use. *Psychol Addict Behav* **21**, 409-414, doi:10.1037/0893-164X.21.3.409 (2007).
- 63 Smith, R. *et al.* Imprecise Action Selection in Substance Use Disorder: Evidence for Active Learning Impairments When Solving the Explore-exploit Dilemma. *Drug and Alcohol Dependence* **215**, 108208 (2020).
- 64 Chrysikou, E. G., Gorey, C. & Aupperle, R. L. Anodal transcranial direct current stimulation over right dorsolateral prefrontal cortex alters decision making during approach-avoidance conflict. *Soc Cogn Affect Neurosci* **12**, 468-475, doi:10.1093/scan/nsw140 (2017).

Supplementary Materials:

Long-term stability of computational parameters during approach-avoidance conflict in a transdiagnostic psychiatric patient sample

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Additional methods information

Approach-avoidance conflict (AAC) task

The AAC task used here is identical to that used in our previous paper (1). Prior to performing the task, participants received detailed instructions (also provided as an appendix in our previous paper) 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** within the main text). 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

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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.

The affective image-sound combinations were gathered from the International Affective Picture System [IAPS] (2), International Affective Digitized Sounds [IADS] (3), and other freely available audio files (see further description in previous reports using this task; (4, 5)). The “reward” included 0, 2, 4, or 6 points presented along with a trumpet sound. The specific task

instructions and stimuli used for the AAC task are provided as an appendix in our original paper (1). There were five trial types (see **Figure 1** within the main text), 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 (4, 6), 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 (7, 8), which could suggest similar motivational influences. Behavioral variables consisted of both chosen avatar position and response times (RTs; i.e., time to initial button press) during each trial. Participants were also asked to fill out the same post-task Likert scale questionnaire as in our previous study, which asked about their experience during the task (these questions are listed in **Table 4** within the results section of the main manuscript).

Computational model description

To model behavior on the AAC task described above, we adopted a Markov decision process model under the active inference framework (9-11). 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**:

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

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

Please note that when the dot ($\cdot$) notation is applied to matrices in these and other model equations, this indicates transposed matrix multiplication. Also note that the time index t refers to time points *about* which an individual holds beliefs, where beliefs about each time point can be updated after each new observation. For example, before an observation an individual might have a (often uncertain) belief about the state (and therefore outcomes) at $t = 2$, and will update their beliefs about the state at $t = 2$ after a new observation. In the active inference literature these beliefs *about* time points are often instead denoted with the Greek letter tau (τ) in order to distinguish them from the times (t) *at* which new observations are presented (for details, see (12)).

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 $\mathbf{B}$ 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:

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

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:

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

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

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 (13, 14). For a more detailed description and derivation of the associated belief update equations, see (9, 10, 15); 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

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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, 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

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combinations was 0. Analogous matrices defined the probabilities associated with each of the other trial types, which are depicted in **Figure S1**.

Figure S1. 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

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more details regarding the associated mathematics, see (10, 16). 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.

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 $\mathbf{C}$ 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 $\mathbf{D}$ 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 $\mathbf{D}$ 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 (17). First, each

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.

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 (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 at hand (18). 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 (19).

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 $\beta = 1$. While other prior values could have been chosen, 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 (-)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.

In our previous paper, 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:

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

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 (20, 21)) showed that this model performed worse than the 2-parameter model (protected exceedance probability = 1). Parameters were recoverable for the 2-parameter model, as indicated by simulations confirming that estimated parameter values approached true parameter values across 46 representative combinations present in participant data. Specifically, the Pearson correlation between true and estimated decision uncertainty values in these simulations was $r = .94$, and that for EC values was $r = .9$. We therefore selected this model for our further analyses.

Supplementary Results

Intraclass correlations in model parameters by group

ICCs for β by group were as follows:

HCS: ICC = .38 ($F(47,47) = 2.2, p = .004$)

DEP/ANX: ICC = .47 ($F(191,191) = 2.8, p < .001$)

SUDs: ICC = .41 ($F(83,83) = 2.4, p < .001$)

ICCs for EC by group were as follows:

HCS: ICC = .60 ($F(47,47) = 4.1, p < .001$)

DEP/ANX: ICC = .48 ($F(191,191) = 2.9, p < .001$)

SUDs: ICC = .48 ($F(83,83) = 2.9, p < .001$)

Intraclass correlations in descriptive task measures

Across participants, ICCs also showed fair to good reliability in each of the five task conditions for both RTs (ICCs between 0.5 and 0.61) and mean chosen runway position (ICCs between 0.4 and 0.56). Similar results were found when examining groups separately. For RTs, HCs: ICCs between 0.44 and 0.57; DEP/ANX: ICCs between 0.5 and 0.62; SUDs: ICCs between 0.52 and 0.63. For mean chosen runway position, reliability differed by group and condition. In HCs, the three conflict conditions showed fair to good reliability (ICCs between 0.58 and 0.62), while reliability in the AV and APP conditions was poor (ICC = 0.23 and -.03, respectively). In contrast, mean chosen runway position in both patient groups showed fair to good reliability in the AV and APP conditions (DEP/ANX: ICCs = 0.63 and 0.47, respectively; SUDs: ICCs = 0.45 and 0.44, respectively), and fair reliability in the three conflict conditions (DEP/ANX: ICCs between 0.41 and 0.44; SUDs: ICCs between 0.42 and 0.51).

Intraclass correlations in clinical measures

From baseline to 1-year follow-up, dimensional measures showed the following single-measure consistency intraclass correlations [ICC(3, 1)]:

PHQ: ICC = .54; $F(246,246) = 3.39, p < .001$

OASIS: ICC = .61; $F(247,247) = 4.07, p < .001$

DAST: ICC = .43; $F(246,246) = 2.50, p < .001$

ASI: ICC = .70; $F(295,295) = 5.69, p < .001$

BIS: ICC = .68; $F(320,320) = 5.32, p < .001$

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BAS-Reward: ICC = .61; $F(320,320) = 4.18, p < .001$

BAS-Fun Seeking: ICC = .64; $F(320,320) = 4.61, p < .001$

BAS-Drive: ICC = .70; $F(320,320) = 5.69, p < .001$

PROMIS-anxiety: ICC = .56; $F(317,317) = 3.52, p < .001$

PROMIS-depression: ICC = .62; $F(316,316) = 4.20, p < .001$

PANASX-positive affect: ICC = .60; $F(320,320) = 4.0, p < .001$

PANASX-negative affect: ICC = .62; $F(320,320) = 4.32, p < .001$

These ICCs generally indicated that these measures had fair to good reliability over the 1-year period.

Comparison of symptoms in participants who did and did not complete the follow-up visit

In both the matched and full samples, two-sample t-tests did not show significant differences in depression or anxiety scores (PHQ and OASIS) at baseline in those who did vs. did not return for the follow-up visit. Those who completed the follow-up visit did have significantly lower substance use symptom severity (DAST) at baseline than those who did not (matched sample: $t(95) = 3.61, p < .001$; full sample: $t(271) = 4.95, p < .001$).

Relationship between model parameters and demographic variables in the full sample at follow-up

The EC parameter was negatively correlated with age scores ($r = -.11, p = .04$), did not differ by sex, and was positively correlated with WRAT scores ($r = .19, p < .001$). The β parameter was positively correlated with age ($r = .14, p = .01$), did not differ by sex, and negatively correlated with WRAT scores ($r = -.25, p < .001$).

Model parameter group difference analyses in the full sample

Here we present group difference results for the full sample (see **Figure 3**, main text), based on identical LMEs including sex, group, and their interactions with session.

An LME revealed main effects of group ($F(2,472) = 10.75, p < .001$) and time ($F(1,377) = 19.01, p < .001$) on β values. Post-hoc contrasts revealed that these effects reflected higher values in SUDs than in HCs ($p < .001$, Cohen's $d = .60$) and DEP/ANX ($p < .001, d = .22$) and lower values at 1-year follow up than at baseline ($p < .001$); effects of sex, and interactions between group and sex or time were non-significant.

There was a main effect of group ($F(2,473) = 11.17, p < .001$) and sex ($F(1,451) = 9.61, p = .002$) on EC, as well as a group by sex interaction ($F(2,459) = 4.70, p = .01$). Post-hoc contrasts revealed that the main effects reflected higher EC in females ($p = .002$) and greater EC in HCs than in both DEP/ANX ($p = .007, d = .23$) and SUDs ($p < .001, d = .76$), as well as greater in DEP/ANX than SUDs ($p = .007, d = .52$). The interaction reflected significant differences between all groups in females ($p < .001$ for each), but no significant differences between groups in males (ps between .24 and .51). There was no effect of time or interaction between group and time.

Standard descriptive analyses in the matched sample

Descriptive statistics for task-related self-report and traditional performance variables (RT, approach behavior) are provided in **Table S1** and **Table S2**; for histograms of approach-

avoidance behavior by group and condition, see **Figure S2**. In identical LMEs to those performed above, average RTs across trial types were significantly faster in the 1-year follow-up compared to baseline ($F(1,216) = 8.54, p = .004$); effects of sex and group (as well as their interaction with time) were non-significant. When analyzing separately by condition, this same pattern was observed in the three conflict conditions. However, the two non-conflict conditions showed a different pattern. The AV condition showed a main effect of group ($F(2,275) = 5.30, p = .006$), but no effect of time or other model terms. The main effect of group reflected faster RTs in HCs than in SUDs ($p = .002$) and DEP/ANX ($p = .01$). The APP condition showed no significant effects, although we note marginal results for group and time ($p = .056$ and $.054$, respectively), suggesting faster RTs in HCs than SUDs ($p = .02$) and faster RTs at 1-year follow-up ($p = .054$). We note that this effect of group was significant in the full sample ($p = .005$), suggesting that this marginal effect reflected reduced power. Other results in the full sample showed a similar pattern as reported here (see below).

In identical LMEs to those performed above, average chosen runway position across the three conflict conditions showed greater approach behavior in males than females ($F(1,269) = 7.46, p = .007$). There was also an effect of group ($F(2,275) = 2.72, p = .04$), reflecting less approach behavior in HCs than in DEP/ANX and SUDs ($p = .02$ and $.03$, respectively). The same pattern was also found when analyzing the three conflict conditions separately, with the exception that the effect of group was only marginal in the CONF6 condition ($F(2,275) = 2.56, p = .08$), but showed the same pattern (i.e., less approach in HCs than in DEP/ANX and SUDs; $p = .04$ and $.05$, respectively). Within AV trials, we observed an effect of group ($F(2,273) = 8.21, p < .001$),

reflecting greater avoidance behavior in HCs than in both SUDs ($p < .001$) and DEP/ANX (marginal; $p = .07$), and greater avoidance in DEP/ANX than in SUDs ($p = .003$). We note that the difference between HCs and DEP/ANX was significant in the full sample ($p = .02$), suggesting this marginal result was due to low power in the matched sample. We also note a marginal effect of sex ($F(1,169) = 3.53$, $p = .06$; suggesting greater avoidance in females). No significant effects were observed in APP trials, although we note a marginal effect of time ($F(1,223) = 3.07$, $p = .08$), suggesting greater approach at 1-year follow-up. We note that there was a main effect of group in the full sample for APP trials, reflecting greater approach behavior in HCs than in SUDs ($p = .001$) and greater approach in DEP/ANX than in SUDs ($p = .02$). In other cases, similar results were found in the full sample (see supplementary results).

As in our previous study, we also report analyses of within-subject choice variability within the Appendix, and confirm its expected relationship with our decision uncertainty model parameter. Within-subject variability also showed expected group differences and effects of time; that is, greater variability in SUDs than in HCs and DEP/ANX (strongest in the AV and CONF6 conditions), and reduced choice variability over time.

Standard descriptive analyses in the full sample

In identical LMEs to those preformed above, when averaging RTs across trial types there was a main effect of group ($F(2,477) = 4.41$, $p = .01$) and time ($F(1,352) = 8.43$, $p = .004$; significantly faster in the 1-year follow-up compared to baseline). Post-hoc contrasts revealed that RTs were significantly faster in HCs than in both SUDs ($p = .003$) and DEP/ANX ($p = .04$). Effects of sex

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and group (as well as their interaction with time) were non-significant. When analyzing separately by condition, the three conflict conditions only showed the effect of time (ps between .002 and .03). However, the two non-conflict conditions showed a different pattern. The AV condition showed a main effect of group ($F(2,478) = 9.45, p < .001$) and sex ($F(1,457) = 5.48, p = .02$; faster RTs in females), and only a marginal effect of time ($F(1,357) = 3.60, p = .06$), but no interactions between group and sex or time. The main effect of group reflected faster in RTs in HCs than in SUDs ($p < .001$) and DEP/ANX ($p < .001$). The APP condition only showed a significant effect of group ($F(2,477) = 5.40, p = .005$), reflecting faster RTs in HCs than both SUDs ($p = .004$) and DEP/ANX (marginally, $p = .05$). and marginally faster RTs in DEP/ANX than SUDs ($p = .054$).

Table S1. Summary statistics for task reaction times (Mean (SD)) at baseline and follow-up

<u>Full Sample</u>	HCs (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)
Avoid Condition (Baseline)	1.19 (0.24)	1.41 (0.34)	1.43 (0.34)
Avoid Condition (1-year follow-up)	1.20 (0.33)	1.33 (0.37)	1.40 (0.33)
Approach Condition (Baseline)	1.11 (0.22)	1.28 (0.35)	1.23 (0.38)

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Approach Condition (1-year follow-up)	1.11 (0.27)	1.20 (0.36)	1.25 (0.38)
Conflict: 2 points (Baseline)	1.20 (0.34)	1.28 (0.36)	1.26 (0.39)
Conflict: 2 points (1-year follow-up)	1.14 (0.29)	1.22 (0.39)	1.26 (0.36)
Conflict: 4 points (Baseline)	1.18 (0.34)	1.26 (0.36)	1.20 (0.35)
Conflict: 4 points (1-year follow-up)	1.09 (0.28)	1.17 (0.34)	1.23 (0.41)
Conflict: 6 points (Baseline)	1.20 (0.37)	1.28 (0.36)	1.20 (0.34)
Conflict: 6 points (1-year follow-up)	1.09 (0.23)	1.19 (0.35)	1.22 (0.37)
<u>Propensity Matched</u>	HCS (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)
Avoid Condition	1.19 (0.24)	1.37 (0.32)	1.41 (0.33)

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(Baseline)			
Avoid Condition (1-year follow-up)	1.21 (0.33)	1.29 (0.34)	1.38 (0.32)
Approach Condition (Baseline)	1.11 (0.22)	1.25 (0.33)	1.19 (0.36)
Approach Condition (1-year follow-up)	1.11 (0.27)	1.17 (0.34)	1.19 (0.32)
Conflict: 2 points (Baseline)	1.20 (0.34)	1.26 (0.36)	1.21 (0.33)
Conflict: 2 points (1-year follow-up)	1.14 (0.29)	1.18 (0.36)	1.19 (0.30)
Conflict: 4 points (Baseline)	1.18 (0.34)	1.23 (0.33)	1.15 (0.28)
Conflict: 4 points (1-year follow-up)	1.09 (0.28)	1.13 (0.32)	1.16 (0.31)
Conflict: 6 points (Baseline)	1.20 (0.37)	1.26 (0.35)	1.12 (0.24)

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Conflict: 6 points (1-year follow-up)	1.09 (0.23)	1.16 (0.34)	1.15 (0.36)
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In identical LMEs to those preformed above, average chosen runway position across the three conflict conditions showed greater approach behavior in males than females ($F(1,450) = 9.71, p = .002$), as well as an effect of group ($F(2,472) = 7.67, p < .001$) and a group by sex interaction ($F(2,458) = 4.84, p = .008$). The main effect reflected less approach behavior in HCs than in DEP/ANX and SUDs ($p = .01$ and $p < .001$, respectively), and less approach behavior in DEP/ANX than SUDs ($p = .04$). The interaction reflected the presence of all group differences stated above in females ($ps < .001$ to $.004$), but the absence of these effects in males (ps between $.56$ and $.77$). The same pattern was found when analyzing each conflict condition separately, with the exception that the difference between SUDs and DEP/ANX in CONF4 was only marginal ($p = .06$). Within AV trials, we observed an effect of group ($F(2,476) = 17.00, p < .001$), reflecting greater avoidance behavior in HCs than in both SUDs ($p < .001$) and DEP/ANX ($p = .02$). and greater avoidance in DEP/ANX than in SUDs ($p < .001$). Within APP trials, we observed an effect of group ($F(2,472) = 6.00, p = .002$), reflecting greater approach behavior in HCs than in SUDs ($p = .001$) and greater approach in DEP/ANX than in SUDs ($p = .02$).

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Figure S2. Histograms showing mean runway position by group and condition. In the “Avoid Threat” condition, higher values (toward the right) on the x-axis indicate greater avoidance behavior. In all other conditions, higher values on the x-axis indicate greater approach behavior. As can be seen here, healthy controls (HCs) tend to approach vs. avoid completely (always move all the way toward the left or the right) and tend to do so in roughly equivalent proportions within the conflict conditions. In contrast, individuals with depression/anxiety (DEP/ANX) and substance use disorders (SUDs) tend to avoid less, and they more often choose values in the middle of the runway.

Table S2. Summary statistics for chosen runway position (Mean (SD)) at baseline and follow-up[†]

<u>Full Sample</u>	HCS (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)
Avoid Condition (Baseline)	9.60 (0.81)	9.06 (1.61)	8.01 (2.24)
Avoid Condition (1-year follow-up)	9.48 (1.50)	9.19 (1.49)	8.50 (1.78)
Approach Condition (Baseline)	9.83 (0.42)	9.25 (1.49)	9.23 (1.19)
Approach Condition (1-year follow-up)	9.65 (1.22)	9.37 (1.54)	9.21 (1.36)
Conflict: 2 points (Baseline)	6.90 (3.16)	7.12 (2.88)	7.99 (2.36)
Conflict: 2 points (1-year follow-up)	6.09 (3.68)	7.21 (3.19)	8.27 (2.31)
Conflict: 4 points (Baseline)	7.19 (3.28)	7.51 (2.86)	8.22 (2.35)

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Conflict: 4 points (1-year follow-up)	6.25 (3.72)	7.41 (3.21)	8.38 (2.49)
Conflict: 6 points (Baseline)	7.43 (3.25)	7.67 (2.84)	8.38 (2.32)
Conflict: 6 points (1-year follow-up)	6.43 (3.71)	7.51 (3.27)	8.50 (2.40)
<u>Propensity Matched</u>	HCS (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)
Avoid Condition (Baseline)	9.60 (0.81)	9.17 (1.54)	8.19 (2.18)
Avoid Condition (1-year follow-up)	9.47 (1.51)	9.20 (1.51)	8.76 (1.67)
Approach Condition (Baseline)	9.83 (0.42)	9.21 (1.60)	9.30 (1.19)
Approach Condition (1-year follow-up)	9.64 (1.23)	9.43 (1.45)	9.58 (0.98)
Conflict: 2 points	6.90 (3.16)	7.08 (2.95)	7.94 (2.62)

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(Baseline)			
Conflict: 2 points (1-year follow-up)	6.18 (3.67)	7.35 (3.20)	8.17 (2.85)
Conflict: 4 points (Baseline)	7.19 (3.28)	7.49 (2.91)	8.04 (2.69)
Conflict: 4 points (1-year follow-up)	6.34 (3.71)	7.51 (3.24)	8.11 (3.04)
Conflict: 6 points (Baseline)	7.43 (3.25)	7.62 (2.90)	8.36 (2.66)
Conflict: 6 points (1-year follow-up)	6.51 (3.71)	7.53 (3.30)	8.06 (2.91)

† 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.

Post-hoc analyses of within-subject variability

Based on the group differences we observed in decision uncertainty, as in our previous study we performed post-hoc analyses of descriptive measures of behavioral variability. While not examined in previous studies, longitudinally stable differences in behavioral variability are

implied by our modeling results. **Table S3** 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 a similar pattern seen in the decision uncertainty parameter.

Matched Sample

In LMEs examining variability (standard deviation) in chosen runway position across the three conflict conditions, there was a main effect of time ($F(1,242) = 12.00, p < .001$; less variability at 1-year follow-up). There was no main effect group or sex, or interactions between group and either sex or time). The same pattern was found when analyzing CONF2 and CONF4 separately; however, in CONF6 there was an additional effect of group ($F(2,267) = 5.16, p = .006$), reflecting greater variability in SUDs than in HCs and DEP/ANX ($p = .003$ and $.005$, respectively). Within AV trials, we observed an effect of group ($F(2,272) = 13.48, p < .001$), reflecting greater variability in SUDs than in both DEP/ANX and HCs ($p < .001$ each) and greater variability in DEP/ANX than in HCs ($p = .01$). There were no other main effects or interactions, although we note a marginal effect of sex ($F(1,268) = 3.67, p = .06$) suggesting greater variability in males. Within APP trials, we observed a main effect of time ($F(1,236) = 6.61, p = .01$; less variability at 1-year follow-up). We also note a marginal effect of group ($F(2,272) = 2.44, p = .09$), suggesting the effect of group reflected greater variability in SUDs than in both HCs ($p = .03$). This effect was significant in the full sample, suggesting this marginal result may be due to low power given the small sample size for SUDs in the matched

sample.

Full Sample

In LMEs examining variability (standard deviation) in chosen runway position across the three conflict conditions, there were main effects of group ($F(2,462) = 6.30, p = .002$) and time ($F(1,392) = 15.85, p < .001$; less variability at 1-year follow-up). The main effect of group reflected greater variability in SUDs than in HCs and DEP/ANX ($p = .001$ and $.006$, respectively). There was no main effect of sex or interactions between group and either sex or time. The same pattern was found when analyzing each conflict condition separately, with the exception that the difference between SUDs and DEP/ANX was only marginal in the CONF4 condition ($p = .07$). Within AV trials, we observed an effect of group ($F(2,471) = 26.60, p < .001$), reflecting greater variability in SUDs than in both DEP/ANX and HCs ($p < .001$ each) and greater variability in DEP/ANX than in HCs ($p = .003$). There were no other main effects or interactions. Within APP trials, we observed main effects of of group ($F(2,468) = 8.81, p < .001$) and time ($F(1,384) = 4.60, p = .03$; less variability at 1-year follow-up), The effect of group reflected greater variability in SUDs than in both HCs and DEP/ANX ($p < .001$ each).

The decision uncertainty parameter was also significantly correlated with within-subject SDs across conditions, as would be expected (see **Figure S3**).

Figure S3. Pearson correlations between parameter estimates (full sample) and within-subject choice variability (per task condition). The ‘X’ over a correlation indicates a p-value greater than .05. Higher decision uncertainty is associated with greater variability, as expected. Emotional conflict is negatively associated with variability in the ‘avoid threat’, suggesting that those more driven to avoid threat are less uncertain about what to do.

Table S3. Summary statistics for within-subject variability (SD) in chosen runway position (Mean (SD))

Full Sample	HCS (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)
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Avoid Condition (Baseline)	0.64 (0.99)	0.89 (1.17)	1.48 (1.27)
Avoid Condition (1-year follow-up)	0.40 (0.91)	0.87 (1.15)	1.54 (1.26)
Approach Condition (Baseline)	0.38 (0.75)	0.73 (1.11)	0.96 (1.15)
Approach Condition (1-year follow-up)	0.41 (0.92)	0.56 (1.05)	0.80 (1.21)
Conflict: 2 points (Baseline)	1.15 (1.27)	1.38 (1.25)	1.38 (1.24)
Conflict: 2 points (1-year follow-up)	0.74 (1.14)	0.94 (1.23)	1.16 (1.21)
Conflict: 4 points (Baseline)	0.80 (1.01)	1.09 (1.19)	1.13 (1.17)
Conflict: 4 points (1-year follow-up)	0.53 (1.08)	0.84 (1.18)	0.85 (1.16)
Conflict: 6 points	0.86 (1.09)	1.11 (1.26)	1.20 (1.22)

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(Baseline)			
Conflict: 6 points (1-year follow-up)	0.60 (1.08)	0.73 (1.12)	1.07 (1.25)
<u>Propensity Matched</u>	HCs (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)
Avoid Condition (Baseline)	0.64 (0.99)	0.84 (1.17)	1.48 (1.18)
Avoid Condition (1-year follow-up)	0.41 (0.92)	0.85 (1.17)	1.45 (1.24)
Approach Condition (Baseline)	0.38 (0.75)	0.71 (1.09)	0.77 (1.09)
Approach Condition (1-year follow-up)	0.42 (0.92)	0.55 (1.07)	0.47 (0.85)
Conflict: 2 points (Baseline)	1.15 (1.27)	1.32 (1.25)	1.22 (1.29)
Conflict: 2 points (1-year follow-up)	0.75 (1.15)	0.90 (1.17)	0.94 (1.08)

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Conflict: 4 points (Baseline)	0.80 (1.01)	1.06 (1.14)	0.97 (1.26)
Conflict: 4 points (1-year follow-up)	0.54 (1.09)	0.78 (1.15)	0.57 (1.04)
Conflict: 6 points (Baseline)	0.86 (1.09)	1.04 (1.22)	0.93 (1.26)
Conflict: 6 points (1-year follow-up)	0.57 (1.07)	0.68 (1.09)	1.04 (1.26)

Group differences in post-task self-report questions

As additional confirmation of behavioral results, we also used LMEs to assess group differences in self-reported approach-avoidance motivations, anxiety, and decision difficulty during the task. Descriptive values for all post-task self-report questions by group are shown in the **Table S4**.

Matched Sample

For self-reported task anxiety, no significant effects were observed. Although, we note marginal effects of sex, group, and time (ps between .07 and .09), which were significant in the full sample (greater anxiety in females, greater anxiety at baseline, and greater anxiety in DEP/ANX than SUDs; see below).

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For self-reported decision difficulty on the task, there were main effects of time ($F(1,240) = 16.64, p < .001$; greater at baseline) and group $F(2,271) = 3.8, p = .02$). The main effect of group reflected lower decision difficulty in HCs than in both SUDs and DEP/ANX ($p = .03$ and $.01$, respectively). Similar results were found in the full sample (see below).

For self-reported approach motivations on the task, there was a main effects of sex ($F(1,268) = 5.36, p = .02$; less approach in females). We also note a marginal effect of group ($p = .06$), which was significant in the full sample (see below). This suggested less approach motivations in HCs than in both SUDs and DEP/ANX.

For self-reported avoidance motivations on the task, no significant effects were observed.

However, we note marginal effects of sex and its interaction with group ($ps = .05$ and $.06$, respectively), which were significant in the full sample (indicating greater avoidance in females; and greater avoidance in HCs than SUDs and DEP/ANX in females, while no groups differed in males; see below).

Full Sample

For self-reported anxiety, there were main effects of sex ($F(1,448) = 7.16, p = .007$; greater in females), time ($F(1,380) = 7.05, p = .008$; greater at baseline), and group $F(2,470) = 3.52, p = .03$). The main effect of group reflected greater anxiety in DEP/ANX than SUDs ($p = .008$).

For self-reported decision difficulty, there were main effects of time ($F(1,382) = 20.60, p < .001$; greater at baseline) and group $F(2,468) = 5.0, p = .007$). The main effect of group reflected lower

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decision difficulty in HCs than in both SUDs and DEP/ANX ($p = .002$ and $.02$, respectively).

For self-reported approach behavior, there were main effects of sex ($F(1,448) = 7.18, p = .008$; less approach in females) and group ($F(2,470) = 5.55, p = .004$). The main effect of group reflected less approach behavior in HCs than in both SUDs and DEP/ANX ($p = .001$ and $.04$, respectively).

For self-reported avoidance behavior, there were main effects of sex ($F(1,447) = 8.04, p = .005$; greater in females), group ($F(2,468) = 3.12, p = .04$), and their interaction ($F(2,455) = 3.33, p = .04$). The main effect of group reflected greater avoidance in HCs than SUDs ($p = .02$). The interaction reflected that HCs showed greater avoidance than SUDs and DEP/ANX in females ($p < .001$ and $p = .005$, respectively), while no groups differed in males.

Table S4. Task-specific self-report questionnaire summary statistics (Mean (SD)) at baseline and follow-up*

<u>Full Sample</u>	HCs (N = 49)	DEP/ANX (N = 192)	SUDs (N = 84)
1. I found the POSITIVE pictures enjoyable (Baseline)	5.08 (1.87)	5.07 (1.68)	5.25 (1.58)
1. I found the POSITIVE pictures enjoyable (1-year follow-up)	5.27 (1.51)	4.99 (1.55)	5.01 (1.56)
2. The NEGATIVE pictures made me feel anxious Or	4.56 (1.83)	4.81 (1.97)	4.14 (2.05)

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uncomfortable (Baseline)			
2. The NEGATIVE pictures made me feel anxious Or uncomfortable (1-year follow-up)	4.00 (1.66)	4.52 (2.05)	3.79 (1.84)
3. I often found it difficult to decide which outcome I wanted (Baseline)	2.17 (1.65)	2.49 (1.79)	2.58 (1.69)
3. I often found it difficult to decide which outcome I wanted (1-year follow-up)	1.47 (0.92)	2.08 (1.65)	2.12 (1.65)
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS (Baseline)	4.42 (2.60)	4.48 (2.44)	5.15 (2.04)
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS (1-year follow-up)	3.96 (2.73)	4.78 (2.55)	5.46 (1.97)
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS	3.27 (2.52)	3.05 (2.23)	2.58 (2.06)

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(Baseline)			
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS (1-year follow-up)	3.76 (2.73)	3.30 (2.41)	2.54 (2.00)
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture (Baseline)	5.33 (1.96)	5.15 (1.99)	5.96 (1.56)
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture (1-year follow-up)	5.12 (2.26)	4.95 (2.14)	5.71 (1.44)
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself (Baseline)	3.52 (2.01)	3.20 (2.04)	2.49 (1.73)
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself (1-year follow-up)	3.27 (2.03)	3.46 (2.13)	3.11 (1.99)

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8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures (Baseline)	3.50 (1.79)	3.58 (2.08)	2.87 (1.81)
8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures (1-year follow-up)	3.43 (2.01)	3.72 (2.12)	3.46 (1.99)
<u>Propensity Matched</u>	HCs (N = 48)	DEP/ANX (N = 121)	SUDs (N = 29)
1. I found the POSITIVE pictures enjoyable (Baseline)	5.08 (1.87)	5.07 (1.72)	5.07 (1.69)
1. I found the POSITIVE pictures enjoyable (1-year follow-up)	5.31 (1.49)	4.92 (1.58)	4.97 (1.72)
2. The NEGATIVE pictures made me feel anxious Or uncomfortable (Baseline)	4.56 (1.83)	4.73 (1.91)	3.55 (2.16)
2. The NEGATIVE pictures made me feel anxious Or uncomfortable (1-year follow-up)	3.96 (1.65)	4.43 (2.07)	3.66 (1.84)

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3. I often found it difficult to decide which outcome I wanted (Baseline)	2.17 (1.65)	2.41 (1.78)	2.28 (1.62)
3. I often found it difficult to decide which outcome I wanted (1-year follow-up)	1.48 (0.92)	1.97 (1.52)	1.86 (1.66)
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS (Baseline)	4.42 (2.60)	4.55 (2.40)	4.97 (2.21)
4. I always tried to move ALL THE WAY TOWARDS the outcome with the LARGEST REWARD POINTS (1-year follow-up)	4.02 (2.72)	4.84 (2.56)	5.41 (2.29)
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS (Baseline)	3.27 (2.52)	2.83 (2.13)	2.86 (2.18)
5. I always tried to move ALL THE WAY AWAY FROM the outcome with the NEGATIVE PICTURE/SOUNDS (1-	3.81 (2.73)	3.17 (2.44)	2.41 (2.15)

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year follow-up)			
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture (Baseline)	5.33 (1.96)	5.14 (2.01)	5.83 (1.67)
6. When a NEGATIVE picture and sound were displayed, I kept my eyes open and looked at the picture (1-year follow-up)	5.21 (2.20)	5.00 (2.13)	5.59 (1.57)
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself (Baseline)	3.52 (2.01)	3.14 (2.03)	2.31 (1.71)
7. When a NEGATIVE picture and sound were displayed, I tried to think about something unrelated to the picture to distract myself (1-year follow-up)	3.23 (2.03)	3.50 (2.14)	2.93 (2.15)
8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures (Baseline)	3.50 (1.79)	3.61 (2.12)	2.62 (1.82)

8. When a NEGATIVE picture and sound were displayed, I tried other strategies to manage emotions triggered by the pictures (1-year follow-up)	3.48 (2.00)	3.82 (2.11)	3.66 (2.14)
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***All ratings were on a scale of 1-7.**

Exploratory analysis of longitudinal symptom prediction

Our result in the main text that higher EC values at baseline predicted larger increases (or smaller decreases) in behavioral inhibition over time prompted us to further assess effects of group and session on BIS scores (Baseline: HCs, mean = 18.1, SD = 3.2; DEP/ANX, mean = 23.7, SD = 3.4; SUDs, mean = 21.0, SD = 3.9; Follow-up: HCs, mean = 18.1, SD = 3.5; DEP/ANX, mean = 23.1, SD = 3.7; SUDs, mean = 19.4, SD = 4.2). An LME revealed main effects of group ($F(2,483) = 75.38, p < .001$) and time ($F(1,358) = 10.09, p < .001$; greater scores at baseline), and a group by time interaction ($F(2,361) = 4.51, p = .01$). The group effect reflected greater BIS scores in DEP/ANX than SUDS and HCs, and greater BIS scores in SUDS than HCs ($p < .001$ each). The interaction reflected significant decreases in BIS scores in DEP/ANX and SUDs ($p = .02$ and $p < .001$, respectively), but no change in HCs.

As the Tulsa 1000 has a large number of clinically relevant measures, for hypothesis generation purposes we also conducted an exploratory analysis of partial correlations between baseline task measures and several available measures (after accounting for their baseline values), including

Patient-Reported Outcomes Measurement Information System (PROMIS) depression and anxiety scales (22), the Behavioral Activation/Inhibition (BIS/BAS) scales (23), the PANAS positive and negative affect scales (24), the Anxiety Sensitivity Index (ASI; (25)), the temporal experience of (anticipatory and consummatory) pleasure scales (TEPS; (26)), and the state-trait anxiety inventory (STAI) scales (27). As can be seen in **Figure S4**, task measures did not show strong predictive relationships with changes in clinical measures over time. However, both lower EC parameter values at baseline and less behavioral avoidance (chosen runway position) in the conflict conditions at baseline weakly predicted reductions in behavioral inhibition over time. Stronger avoidance in the avoid (AV) condition at baseline also weakly predicted greater reductions in negative affect (PANAS) over time (but, as noted in the main text, this was not significant within our LMEs accounting for age, sex, and WRAT scores). Although not shown in the figure, no predictive relationships were found between any task measure and changes in the PHQ, OASIS, or DAST screening measures (i.e., for depression, anxiety, and substance use severity, respectively).

Correlations between baseline task measures and symptom changes at follow-up		*p<.005												
BASELINE MEASURES		ASI	BIS	BAS DRIVE	BAS FUN SEEKING	BAS REWARD	PROMIS ANX	PROMIS DEP	PANAS PA	PANAS NA	TEPS ANTICIPATE	TEPS CONSUME	STAI STATE	STAI TRAIT
	Emotional Conflict (EC)	-0.04	0.18*	0.02	0.04	0.07	0.02	-0.04	-0.02	-0.01	0.07	0.09	0.02	0
	Decision Uncertainty (β)	0.03	0.07	0	-0.01	0.02	0.07	0	0.07	0.09	-0.03	-0.01	-0.04	0.01
	RT Avoid Condition	0.03	-0.12	0	0.01	-0.03	-0.07	-0.06	0	0	-0.01	0.06	-0.06	-0.04
	RT Approach Condition	0.04	0.01	-0.03	-0.06	-0.04	0.01	0.03	0.03	0.02	-0.09	0.02	-0.02	0.03
	RT Conf2 Condition	0.06	0.01	-0.01	-0.01	0.05	0	-0.01	0.03	0.02	-0.01	0.09	-0.03	0.01
	RT Conf4 Condition	0.05	0	-0.01	-0.03	-0.02	-0.01	-0.01	0.01	0.01	-0.02	0.11	-0.05	0
	RT Conf6 Condition	0.02	0.05	0.07	-0.01	0	0.02	0.02	0.04	0.02	-0.05	0.05	0	0.03
	Chosen Position - Avoid Condition	-0.13	0.04	0.04	0.02	0.01	-0.05	-0.06	-0.08	-0.18*	0.03	0.11	0.01	-0.07
	Chosen Position - Approach Condition	-0.04	-0.05	0.07	0.06	0.03	-0.09	0	-0.03	-0.11	0.11	0.1	-0.02	-0.07
	Chosen Position - Conf2 Condition	-0.02	-0.18*	-0.04	-0.06	-0.07	-0.02	0.04	-0.01	-0.02	-0.12	-0.08	0.01	0.01
	Chosen Position - Conf4 Condition	-0.01	-0.2*	-0.03	-0.04	-0.08	-0.02	0.03	0	-0.02	-0.08	-0.07	-0.01	-0.02
	Chosen Position - Conf6 Condition	0.01	-0.19*	0	0	-0.07	-0.01	0.01	0.02	0	-0.05	-0.06	-0.03	-0.02

Figure S4. Exploratory analysis of the ability of baseline task measures (left) to predict longitudinal changes in symptoms from baseline to follow-up (top; after accounting for differences in baseline values). Red stars indicate uncorrected p-values < .005. Measures include the anxiety sensitivity index (ASI), behavioral inhibition and activation scales (BIS/BAS), PROMIS depression and anxiety scales, PANAS positive and negative affect (PA/NA) scales, the temporal experience of (anticipatory and consummatory) pleasure scales (TEPS), and the state-trait anxiety inventory (STAI) scales.

Additional information about short-term test-retest sample

Descriptive behavioral measures for the additional healthy control sample of 30 participants are shown in **Table S5**. This sample had a shorter test-retest interval of approximately 2-3 weeks

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(mean = 17.10 days; SD = 5.18; range: 11-32). There were a few differences between the task used in this sample and the version described in the main text (for more details, see (28)). First, it was conducted during functional magnetic resonance imaging. Second, participants used a joystick instead of key press to move the avatar. Third, the task had 90 trials (as opposed to 60 in the version described in the main text. As a result of having more trials, the avatar could also start in any position on the runway across trials in counterbalanced fashion. Finally, in place of 0, 2, 6, or 6 points per trial, participants were offered small monetary rewards (i.e., 0, 2, 4, or 6 United States' cents).

Table S5. Descriptive results for short-term test-retest sample

<u>Behavioral Measure</u>	Time 1		Time 2	
Model Parameters	Mean	SD	Mean	SD
Emotion Conflict (EC)	3.59	2.93	3.64	2.84
Decision Uncertainty (β)	2.33	2.42	2.08	2.01
Chosen Runway Position	Mean	SD	Mean	SD
Approach Condition	8.91	0.15	8.90	0.16
Avoid Condition	8.88	0.21	8.90	0.22
Conflict: 2 points	5.70	3.28	5.35	3.60
Conflict: 4 points	6.07	3.53	5.92	3.51

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Conflict: 6 points	6.42	3.38	6.26	3.53
Reaction Time	Mean	SD	Mean	SD
Approach Condition	0.95	0.15	0.87	0.14
Avoid Condition	1.04	0.17	0.96	0.21
Conflict: 2 points	1.04	0.29	0.92	0.22
Conflict: 4 points	1.02	0.21	0.90	0.21
Conflict: 6 points	0.97	0.22	0.89	0.19
All trials	1.00	0.18	0.90	0.16