Failure to Identify Robust Latent Variables of Positive or Negative Valence Processing Across Units of Analysis

Supplement 1

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1. Supplemental Methods

1.1. Inclusion and exclusion criteria

Inclusion criteria: (i) individuals presenting to primary care clinics, or self-identified individuals, who were recruited via emails from their respective clinics, or through posted announcements online or in the community, with mood and anxiety problems; (ii) score $\geq$ 10 on the Patient Health Questionnaire-9 (PHQ-9; (1) or $\geq$ 8 on the Overall Anxiety and Impairment Scale (OASIS; (2); (iii) between the ages of 18-55; and (iv) able to provide informed, written consent We expected that inclusion based on elevated anxiety (OASIS) or depression (PHQ-9) scores would yield a sample with a broad range of clinically significant anxiety and depression symptoms and associated functional impairment (see Table S3).

Exclusion criteria: (i) Participants with no telephone or easy access to a telephone; (ii) moderate or severe alcohol or marijuana use disorder according to DSM-5 (3) criteria in the past year; and (iii) all other mild substance use disorders in the past year with the exception of alcohol or marijuana use disorder; (iv) Bipolar I or Psychotic disorders; (v) moderate to severe traumatic brain injury with evidence of neurological deficits, neurological disorders, or severe or unstable

medical conditions that might be compromised by participation in the study (determined by primary care provider); (vi) active suicidal ideation; (vii) characteristics that compromise MRI safety (e.g., metal in body), and (viii) inability to speak English.

1.2. Self-report measures

Overall Anxiety Severity and Impairment Scale (OASIS)

OASIS is a 5-item self-report measure that can be used to assess severity and impairment associated with any anxiety disorder or multiple anxiety disorders (4). The five items measure the frequency and severity of anxiety, as well as level of avoidance, work/school/home interference, and social interference associated with anxiety. The instructions orient the respondent to consider a wide range of anxiety symptoms (e.g., panic attacks, worries, flashbacks) when answering the questions, and the time frame is "over the past week." Respondents select among five different response options for each item, which are coded 0–4 and summed to obtain a total score.

Patient Health Questionnaire (PHQ-9)

PHQ is an instrument for making criteria-based diagnoses of depressive and other mental disorders commonly encountered in primary care. (5). The PHQ-9 is the depression module, which scores each of the 9 DSM-IV criteria as "0" (not at all) to "3" (nearly every day). The total score for the nine items ranges from 0 to 27. PHQ-9 depression severity score is 16 (3 items scored 1, 2 items scored 2, and 3 items scored 3). Scores of 5, 10, 15, and 20 represent cutpoints for mild, moderate, moderately severe and severe depression, respectively.

Positive and Negative Affective Schedule - Trait (PANAS)

The PANAS (6) is a 20-item questionnaire that assesses positive and negative affect using 5-point scales (1 = very slightly/not at all, 5 = extremely). Participants were asked to respond based on how they have felt "during the past week". The PANAS has high internal consistency and temporal stability, and its convergent, discriminant, and construct validity have been confirmed by correlational and factor analyses (7).

Generalized Anxiety Disorder 7-item (GAD-7)

The GAD-7 (8) is a self-report questionnaire designed to screen for generalized anxiety disorder that has strong psychometric properties in both primary care settings and the general population (9). It assesses symptoms of worry (e.g., 'Not being able to stop or control worrying') and general somatic tension (e.g., 'Trouble relaxing'). Items are rated on a 4-point Likert-type scale ranging from 0 (not at all sure) to 3 (nearly every day), where higher scores reflect greater symptom severity.

Mood and Anxiety Symptom Questionnaire - Short Form (MASQ)

The MASQ (10) is a 62-item questionnaire designed to measure symptoms of anxiety and depression. It has four subscales: (1) General Distress Anxious Symptoms (GDA: 11 items), (2) General Distress Depressive Symptoms (GDD: 12 items), (3) Anxious Arousal (AA: 17 items), and (4) Anhedonic Depression (AD: 22 items). Participants indicated the extent to which they experienced symptoms during the past week from 1=not at all to 5=extremely. The MASQ has

adequate convergent and discriminant validity and good internal consistency in student, adult volunteer, and clinical samples (11,12).

Behavioral Inhibition and Activation Scales (BIS/BAS)

The BIS/BAS (13) include 20-items that measure dispositional behavioral inhibition and behavioral activation sensitivities (i.e., avoidance and approach motives, respectively), which are hypothesized to reflect the negative and positive valence systems, respectively. The BAS has three subscales: Drive, Reward Responsiveness, and Fun Seeking. Items are rated on four-point scales (1 = strongly disagree; 4 = strongly agree). Test-retest reliability and convergent, discriminant, and predictive validity of the BIS/BAS have been found to be adequate (13–15).

Sensitivity to Punishment and Sensitivity to Reward Questionnaire (SPSRQ)

The SPSRQ (16) is a 48-item yes-no questionnaire with two subscales designed to measure trait-like dispositions to respond to aversive and rewarding stimuli, respectively. The SPSRQ has demonstrated good construct validity (17) and satisfactory internal consistency and test-retest reliability (16).

Temporal Experience of Pleasure Scale (TEPS)

The TEPS (18) is an 18-item questionnaire measuring anticipatory and consummatory pleasure. Each item is rated on a 6 point scale (e.g., 1=very false for me; 6=very true for me), with 10 items aimed at measuring goal attainment (consummatory pleasure) and 8 items aimed at measuring

motivated approach of goals (anticipatory pleasure) (19). The TEPS has demonstrated good internal consistency and test-retest stability (18,20).

Acceptance, Safety, Escape/Avoidance Scale (AcSEAS)

The AcSEAS is a 12-item questionnaire that measures behavioral strategies for managing uncomfortable situations and feelings. It was developed as a transdiagnostic measure of avoidance. Items are rated on a 5-point Likert scale ranging from 1=not at all typical to 5=very typical. Confirmatory factor analyses showed that the AsSEAS has three factors: acceptance, escape/avoidance, and safety behaviors. The AcSEAS has been used to assess avoidance symptom components of negative valence processing (21).

1.3. Behavioral Measures

International Affective Picture System (IAPS)

A subset of 24 IAPS images was selected to represent pleasant (8 images), unpleasant (8 images), and neutral (8 images) valence categories. On each trial, an image was presented for six seconds, immediately after which, participants rated both their perceived valence of the image and their arousal level in response to the image according to the Self Assessment Manikin (22).

The IAPS task was structured in five 12-trial blocks, with an inter-trial interval (ITI) of 20-26 seconds within each block. Each block contained 5 positive, 5 negative, and 2 neutral images presented in a pseudorandomized order such that no more than two consecutive images were ever of the same valence category. Three unique trial orders were counterbalanced across participants. At the start of the first block, three practice trials were presented to familiarize participants with

the task. All stimuli were presented on a computer screen, and all ITIs contained a fixation cross to which participants were instructed to fixate.

Heart rate (HR) and skin conductance (SCR) were recorded throughout the task using Biopac instrumentation (Lehigh, Pennsylvania). Physiological data were further processed using the Autonomic Nervous System Laboratory (ANSLAB) software (23). Heart rate was recorded with standard limb electrocardiogram leads run through a BIOPAC bioamplifier (S75-01) and a tachometer (S77-26) to visualize beats per minute. Skin conductance responses (SCRs) were recorded using two Ag/AgCl electrodes filled with isotonic electrolyte gel. Electrodes were attached at the middle phalanx of the index and middle fingers of the left hand. A constant voltage of 0.5 V was applied across SCR electrodes using a BIOPAC SCR 100 C amplifier at a gain of 2 mS/V. Skin conductance was recorded continuously at a 1000 Hz sampling rate using AcqKnowledge373 data acquisition software.

For each image we computed the difference between peak skin conductance during image presentation and average skin conductance across a 2 s baseline period immediately preceding image onset. The final summary SCR measurements that were included in the GFA were the average baseline-to-peak differences across each image category (positive, negative, and neutral).

Mirror Tracing Persistence Task (MTPT)

Distress tolerance was measured with a computerized mirror tracing persistence task (MTPT) (24) in which participants were required to trace three different shapes (i.e. a horizontal line first, an L-shape second, and a star shape lastly) by moving a small red dot with a mouse. The movement of

the cursor on the screen was mirrored (i.e., inverted both horizontally and vertically). Moving off the line or pausing for 2 seconds triggered a loud buzzer sound through the headphones and reset the red dot back to the starting point. Participants were given 60 seconds to trace each of the first two shapes. Immediately following the second shape, an on-screen message appeared with a 30 second countdown, warning that the last shape is very difficult and that they may end the task by pressing any key on the keyboard. Participants were told that their performance on the final shape would affect the amount of their reward. The task was discontinued after 5 minutes, regardless of performance.

Persistence was measured as the total task duration prior to the participant either giving up or reaching the five minute limit (~30% of subjects reached the end of the allotted five minutes without giving up). Heart rate change was computed by taking the difference between the average heart rate measured across the first minute of the task and the average heart rate measured during a 5-minute baseline period immediately preceding the onset of the task. Only the first minute of the task was used for this measure in order to maximize sample size, as using longer intervals would lead to a larger number of participants who quit prematurely.

1.4. Neuroimaging Measures

Monetary Incentive Delay Task

The MID task reliably activates neural circuits implicated in reward (e.g., ventral striatum) and loss processing (e.g., anterior insula). Individual differences in positive affective traits are related to the degree of neural activation during reward (but not loss) trials, whereas negative affective traits are associated with activation during loss (but not gain) trials (25). On each trial, participants

were presented with a cue indicating potential gains or losses of ±$0.00, ±$1.00, or ±$5.00. This resulted in six task conditions comprising 15 trials each.

On each trial, participants were presented with one of six cue shapes (cue; 2000 ms), followed by a crosshair (anticipation phase; 2000 ms), after which they were required to respond with a button press during the presentation of a briefly presented white target of variable duration. Target duration was set at 250 ms for all participants at the beginning of the task, and titrated throughout the task such that participants succeeded on approximately 66% of their target responses. Feedback (outcome phase; 2000 ms) notifying participants how much money they had gained or lost that trial followed the disappearance of the target. A variable inter-trial interval of 2000, 4000, or 6000 ms occurred prior to the next trial onset. On incentive trials, participants could either gain or avoid losing money by pressing the button during target presentation. Prior to entering the scanner, participants were trained and tested for explicit cue comprehension, and shown the cash they could win during the task.

Fear conditioning

For the fear conditioning fMRI task we used a Pavlovian fear learning and extinction paradigm, as in several prior fMRI studies of fear learning in healthy and anxious samples (26–28). During fear acquisition, participants viewed images of two CS+ stimuli and one CS- stimulus (images of rooms with different colored lights). There were 8 trials of each CS+ (16 trials total), 62.5% of which were reinforced with a US (electric shock) and 16 CS- trials. During fear extinction, one of the CS+ stimuli was selected to be extinguished (CS+E) and was no longer paired with the US. Participants viewed 16 trials with CS+E together with 16 CS- trials.

On each trial, a 'context' image of a room with no light was presented for 3 seconds, followed by a 6-second CS image of a room with light. The inter-trial-interval across all phases of the task varied from 12 to 15 seconds. At the end of each phase of the task, participants completed a 'contingency awareness' assessment, in which they rated their perception of the association between the conditioned and unconditioned stimuli on a scale from 1 to 3, where 1 means highly associated, and 3 means not associated.

fMRI acquisition and analysis

High resolution structural (T1-weighted) images and blood oxygenation level-dependent (BOLD, T2*-weighted) functional images were acquired and standard preprocessing procedures applied (see Supplemental Materials). Region of interest (ROI) analyses were conducted on a set of a priori regions of threat-based neurocircuitry for fear conditioning defined using activation peaks from a meta-analysis of human fMRI fear conditioning studies (ventromedial prefrontal cortex (vmPFC), dorsomedial prefrontal cortex (dmPFC), subgenual anterior cingulate cortex (sgACC), dorsal anterior cingulate cortex (dACC), left/right anterior insula, ventral hippocampus, and amygdala, and reward-based neurocircuitry for MID (insula, nucleus accumbens (NAcc), and caudate head) as identified in prior studies (for fear conditioning see: (29,30); MID see (25,31–33)). Meta-analytic ROIs were defined as 5mm spheres around peak activations reported in Fullana et al. (2017). ROIs were defined anatomically based on the Harvard-Oxford atlas provided with FSL for the fear conditioning task. For the MID task, ROIs were parcellated according to the procedure used previously by Drysdale et al. (34).

For fear conditioning, first-level activation analyses were conducted in FSL (35) and included regressors of interest (acquisition: context, CS+, CS- and shock; extinction: context, CS+E, CS-), temporal derivatives, six motion regressors and regressors to censor outlying volumes. We conducted multivariate general linear model (GLM) analyses to extract ROI activations for each task. For fear acquisition and fear extinction, the contrast between CS+ and CS- was calculated for each ROI.

We computed percent signal change for gains and losses as the difference between the average activity in an ROI during anticipatory (the fixation period immediately following a cue) or consummatory (the fixation period immediately following a response) gain or loss intervals, and the mean activity in that ROI across the entire task. These computations were performed separately for each monetary condition ($0, $1, $5). Further, for the consumption condition, ROI activations were computed separately for hit and miss trials, corresponding to successful and unsuccessful performance of the reaction time task, respectively. This resulted in a total of 2 (gain, loss) x 3 ($0, $1, $5) = 6 contrasts for the anticipation condition, and 2 (gain, loss) x 3 ($0, $1, $5) x 2 (hit, miss) = 12 contrasts for the consumption condition, for a total of 18 initial contrasts per ROI. For the final contrasts included in the GFA, for each ROI we computed the average activation across the $1 and $5 conditions and, from that, subtracted the activation in the $0 condition. This was done separately for the following six conditions: anticipation of loss, anticipation of gain, consumption of gain hits, consumption of gain misses, consumption of loss hits, and consumption of loss misses. Therefore, for each MID ROI there were 6 contrasts included in the GFA.

1.5. Testing orthogonality of GFA factor structures

We used an iterative conditional factor-removal procedure to ensure that any intercorrelation among a set of extracted GFs was not greater than that expected due to chance. For each pair of correlation and matching thresholds (see main text, page 13) we evaluated whether intercorrelation among the resulting robust GFs exceeded the maximum intercorrelation expected due to chance, under the assumption that Pearson correlation coefficients should be zero and follow a t-distribution with df=N-2. If the observed intercorrelation exceeded that expected due to chance, we removed the GF that showed the most intercorrelation with all other GFs, and then re-evaluated the intercorrelation. This procedure was repeated iteratively until the observed intercorrelation was less than that expected due to chance. This procedure did not result in the removal of any initially extracted GFs from any of the reported GFAs except the within-task MID and IAPS GFAs (4 and 3 factors removed, respectively).

1.6. Group Factor Valence Quantification

Group factor valence quantification was performed for MID and self-report variable blocks, as they were unique in that the variables they contained could be reasonably split into two roughly equal groups corresponding to positive and negative valence processing, respectively. For the MID variable block, contrasts corresponding to gains (gain1,5 hit - gain0 hit; gain1,5 cue - gain0 cue; gain1,5 miss - gain0 miss) and losses (lose1,5 miss - lose0 miss; lose1,5 cue - lose0 cue; lose1,5 hit - lose0 hit) were given positive and negative valence coefficients, respectively. For the self-report block, valence coefficient assignments were as follows: positive valence coefficients were assigned to the PANAS_PA, BASReward, BASDrive, BASFun, SPSRQRew, TEPS_ant, TEPS_cons, AcSEASAccept, AcSEASSafe, and AcSEASEsAv questionnaires, while negative

valence coefficients were assigned to the PHQtot, OASIStot, GADtot, PANAS_NA, BIS, GDAnx, AnxArous, GDDep, AnDep, and SPSRQPun questionnaires.

Valence scores were computed by taking the sum of products of median factor loadings and their corresponding valence coefficients. By this computation, a GF with a valence score with a large absolute value suggests that that factor reflects differential processing of positive and negative valence information. Note that this result will hold if we flip the signs of the assigned valence coefficients. Valence scores for each GF were then compared against a null distribution, which was generated by randomly shuffling valence coefficients and computing valence scores over 10,000 iterations (Figure S7). Significance was evaluated by determining with the observed valence score fell outside of the 95% confidence interval (i.e., alpha = 0.05, two-tailed), with Bonferroni correction applied to account for multiple comparisons within each variable block.

2. Supplemental Results and Figures

2.1. Data structure and missing data

Table S1 shows different measurements nested under each unit of analysis and the corresponding missing data.

Table S1: Number of variables and N of missing data.
[see Tables at end of document]

2.2. Sample Characteristics

Table S2 summarizes the sample characteristics and medication information of the samples for UCSD and UCLA. The majority of the sample was not taking a psychotropic medication. Table S3 summarizes the self-report-based symptom characteristics *related to the negative and positive valence systems* from each site. After correction for multiple comparisons there were no significant differences between samples. Additionally, there was no significant difference in MINI diagnostic scores for current Major Depressive Disorder (MDD) or Generalized Anxiety Disorder (GAD) between participants who were included in the cross-task GFA (N = 118) and those who were not (N_{GAD} = 107, N_{MDD} = 105) (MDD: X^2 = 0.96, V = 0.07, p = 0.33; GAD: X^2= 0.70, V = 0.06 , p = 0.40).

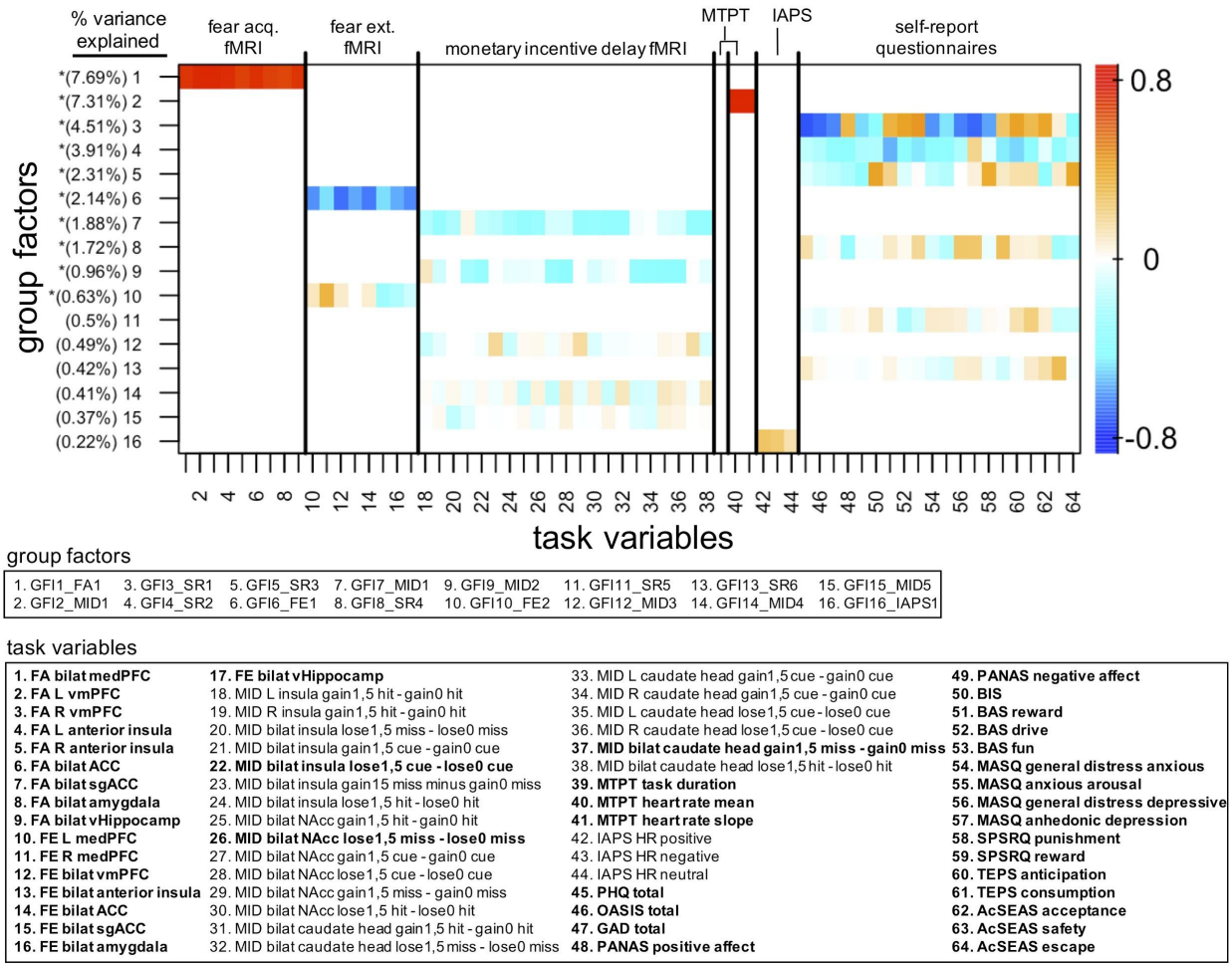
Table S2: Sample Characteristics of subjects enrolled at each site
[see Tables at end of document]

**The total numbers of participants enrolled in the study from each site were 100 and 125 from UCSD and UCLA, respectively. Number of missing samples for demographic and diagnostic info is as follows: age, gender, race:* N_{UCSD}*=2,* N_{UCLA}*=0; education:* N_{UCSD}*=2,* N_{UCLA}*=3; MDD diagnoses:* N_{UCSD}*=0,* N_{UCLA}*=2. Note that while the characteristic data reported here are for all participants enrolled in the study (N=225), subsets of the data ranging from N=118 to N=180 were used for GFA.*

Table S3: Symptom characteristics related to negative and positive valence systems.
[see Tables at end of document]

2.3. Group Factor Analysis with Imputation

One concern is that the main finding of a lack of cross-task or cross-unit latent structure among the variables included in cross-task GFA (Figure 1) is due to a lack of power. Imputation was not used in the main analysis due to the non-random nature of missing data; in each case of missing data (N = 107), data were missing across either entire tasks (e.g., fear acquisition) and/or entire units of analysis (e.g., skin conductance). However, to investigate whether an increase in sample size would affect the overall pattern of results we conducted an additional GFA with expectation-maximization-based imputation (N = 225; Figure S1). While the results should be interpreted with caution due to the non-randomness of the imputed data, we found the same general pattern in which none of the resulting 18 GFs, explaining 31.1% of the total variance, extended across either tasks or units of analysis.



group factors

1. GFI1_FA1	3. GFI3_SR1	5. GFI5_SR3	7. GFI7_MID1	9. GFI9_MID2	11. GFI11_SR5	13. GFI13_SR6	15. GFI15_MID5
2. GFI2_MID1	4. GFI4_SR2	6. GFI6_FE1	8. GFI8_SR4	10. GFI10_FE2	12. GFI12_MID3	14. GFI14_MID4	16. GFI16_IAPS1

task variables

1. FA bilat medPFC	**17. FE bilat vHippocamp**	33. MID L caudate head gain1,5 cue - gain0 cue	**49. PANAS negative affect**
2. FA L vmPFC	18. MID L insula gain1,5 hit - gain0 hit	34. MID R caudate head gain1,5 cue - gain0 cue	**50. BIS**
3. FA R vmPFC	19. MID R insula gain1,5 hit - gain0 hit	35. MID L caudate head lose1,5 cue - lose0 cue	**51. BAS reward**
4. FA L anterior insula	20. MID bilat insula lose1,5 miss - lose0 miss	36. MID R caudate head lose1,5 cue - lose0 cue	**52. BAS drive**
5. FA R anterior insula	21. MID bilat insula gain1,5 cue - gain0 cue	**37. MID bilat caudate head gain1,5 miss - gain0 miss**	**53. BAS fun**
6. FA bilat ACC	**22. MID bilat insula lose1,5 cue - lose0 cue**	38. MID bilat caudate head lose1,5 hit - lose0 hit	**54. MASQ general distress anxious**
7. FA bilat sgACC	23. MID bilat insula gain15 miss minus gain0 miss	**39. MTPT task duration**	**55. MASQ anxious arousal**
8. FA bilat amygdala	24. MID bilat insula lose1,5 hit - lose0 hit	**40. MTPT heart rate mean**	**56. MASQ general distress depressive**
9. FA bilat vHippocamp	25. MID bilat NAcc gain1,5 hit - gain0 hit	**41. MTPT heart rate slope**	**57. MASQ anhedonic depression**
10. FE L medPFC	**26. MID bilat NAcc lose1,5 miss - lose0 miss**	42. IAPS HR positive	**58. SPSRQ punishment**
11. FE R medPFC	27. MID bilat NAcc gain1,5 cue - gain0 cue	43. IAPS HR negative	**59. SPSRQ reward**
12. FE bilat vmPFC	28. MID bilat NAcc lose1,5 cue - lose0 cue	44. IAPS HR neutral	**60. TEPS anticipation**
13. FE bilat anterior insula	29. MID bilat NAcc gain1,5 miss - gain0 miss	**45. PHQ total**	**61. TEPS consumption**
14. FE bilat ACC	30. MID bilat NAcc lose1,5 hit - lose0 hit	**46. OASIS total**	**62. AcSEAS acceptance**
15. FE bilat sgACC	31. MID bilat caudate head gain1,5 hit - gain0 hit	**47. GAD total**	**63. AcSEAS safety**
16. FE bilat amygdala	32. MID bilat caudate head lose1,5 miss - lose0 miss	**48. PANAS positive affect**	**64. AcSEAS escape**

Figure S1. GFA robust factor loadings with expectation-maximization-based imputation of missing data (N=225). Heatmap colors indicate the weight of each task variable loading. Robust group factors are sorted in descending order by mean % variance explained across all groups. Asterisks indicate group factors that contained at least one task variable loading whose 95% credible interval did not contain zero.

2.4. Principal Component Analysis

To validate the group factor analysis (GFA) results, we further conducted a classic PCA to examine if similar latent structures would be revealed from the dataset. We first conducted the parallel analysis to determine the number of principal components to be included in PCA. Figure S2 shows the parallel analysis (36) which revealed that 10 components optimally describe the underlying

correlational structure. The principal components cumulatively accounted for 54% of the variance. The components were ranked based on the relative variance accounted for after varimax-rotation. As shown in Figure S3, components 1 and 3 loaded significantly on ROI activations of fear acquisition and extinction, respectively. Components 2 and 4 loaded significantly on self-report measurements. Other components loaded on IAPS and MID tasks separately. Together, PCA results replicated GFA results by showing that individual tasks loaded on different principal components and do not show a strong shared latent structure.

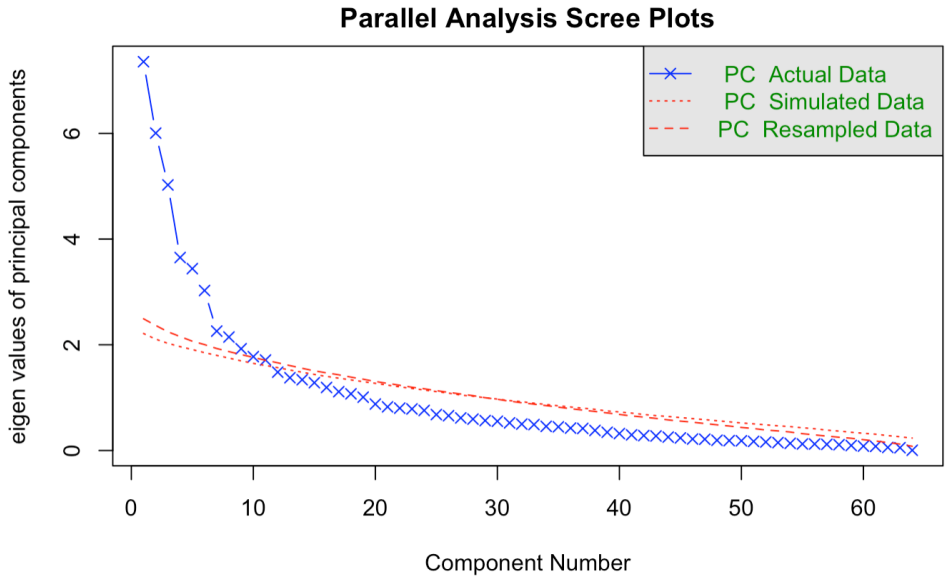


Figure S2. Scree plots of the parallel analysis of PCA components, showing that 10 components optimally describe the underlying correlational structure.

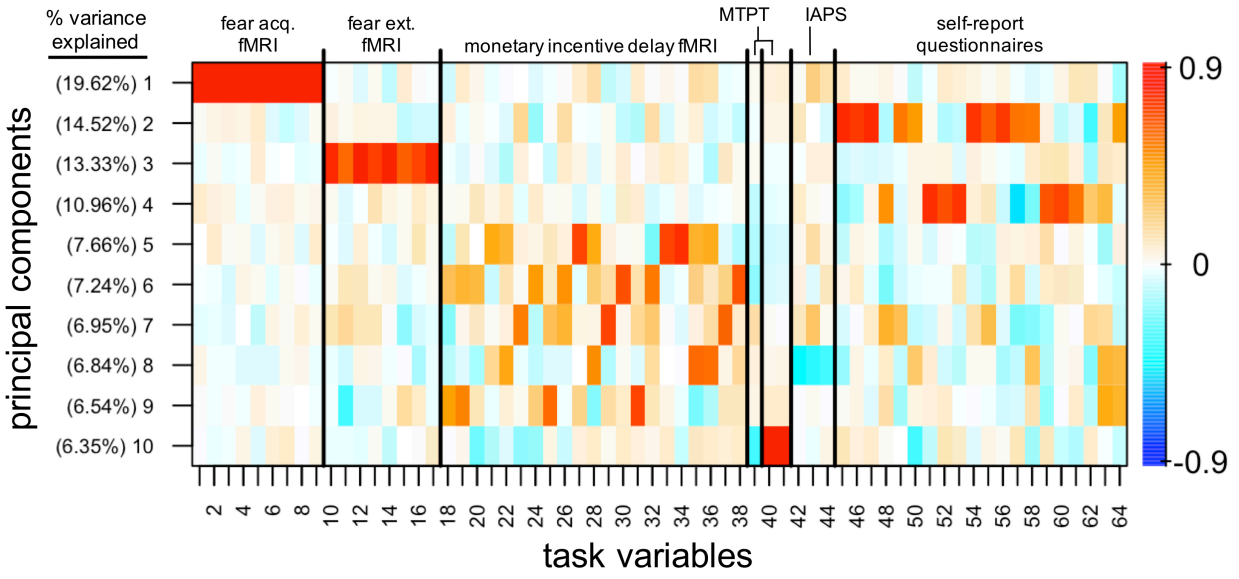


Figure S3. A heatmap showing loadings of variables to PCA components. Ten orthogonally rotated principal components are shown on the vertical axis. Task variables are ordered from left to right in the same order of the GFA variables in Figure 1 of the main text. More saturated blue colors indicate stronger negative loading weights and more saturated red colors indicate stronger positive loading weights.

2.5. Network graphical models

To visualize the correlations between variables in different units of analysis, we conducted a graphical model in R with the function of qgraph (37). We entered all 64 variables into the model with the specification of which variable belongs to which group. Figure S4 shows the model with a circular layout, which enables us to show the relative strength of significant Pearson correlation coefficients (evaluated at alpha = 0.05, unadjusted) within and between tasks and units of analysis. Alpha was not adjusted for multiple comparisons given the exploratory purpose of the network model. While a small number (i.e., 4 pairs) of significant cross-task correlations were observed between the MID, self-report, and MTPT variable blocks, the overwhelming majority of significant correlations were observed within tasks and units of analysis. Overall, these results are consistent with the lack of cross-task and cross-unit latent structure identified by GFA. See the

"significant_pairwise_corrs" worksheet in the supplemental document "peng_knotts_et_al_correlation_tables.xlsx" for a list of all significant pairwise correlations.

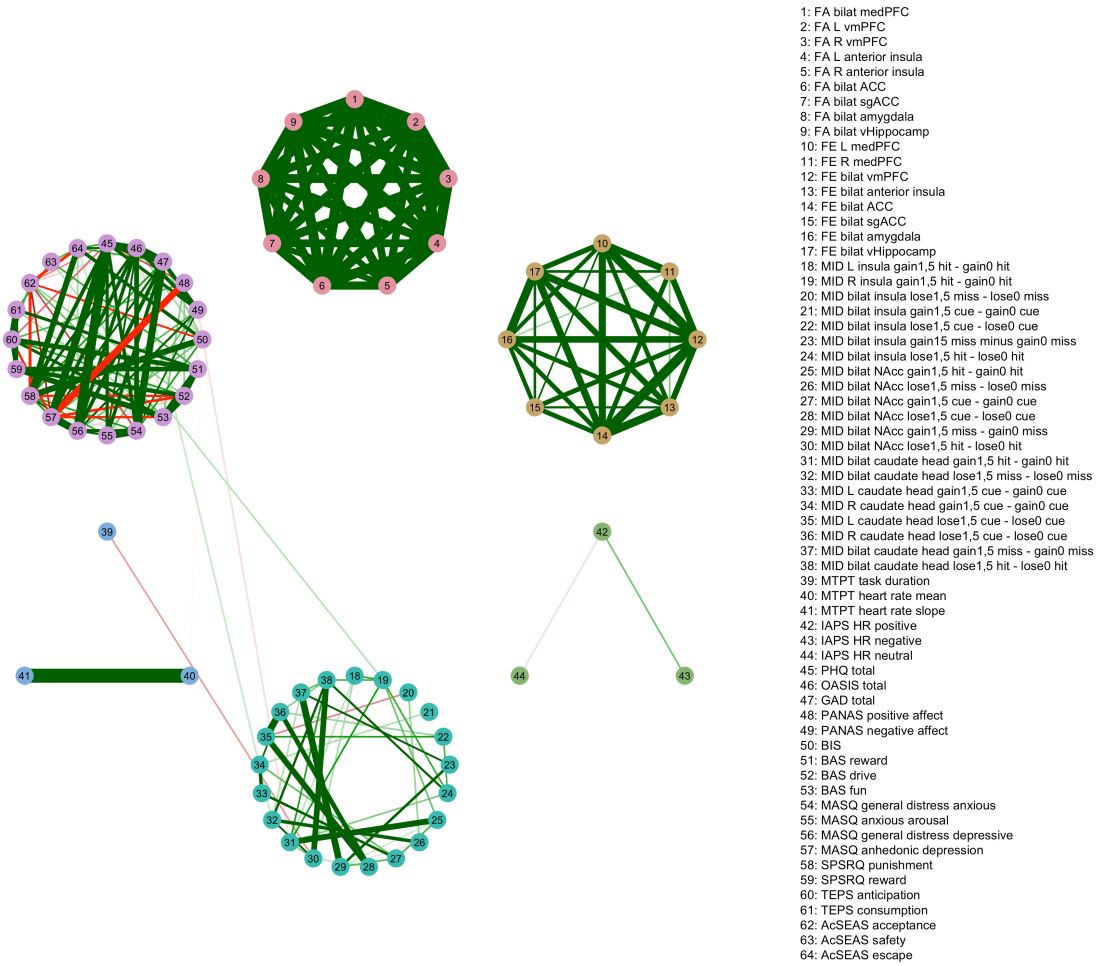


Figure S4. A visualization of the correlation matrix of the current dataset from a graphical network model. Each node corresponds to a variable and each line corresponds to a significant correlation (Pearson coefficient $p < 0.05$, uncorrected) between two variables. Green lines show positive correlations, red lines show negative correlations, and line width and color saturation correspond to the absolute value of the correlations such that higher correlations are indicated by thicker and more saturated lines. A key for variable names is shown on the right.

2.6. Within-task MID and self-report GFAs

In addition to within-task GFAs for the fear conditioning, the IAPS, and MTPT variable blocks (main text), we ran within-task GFAs for the MID and self-report variable blocks (Figure S5). The numbers of study participants with complete data for the MID and self-report variables blocks were 182 and 220, respectively. Within-task GFAs identified 4 group factors (GFs) explaining 10.73 % of the total variance in the MID variable block (Figure S5a), and 8 GFs explaining 48.9 % of the total variance in the self-report variable block Figure S5b).

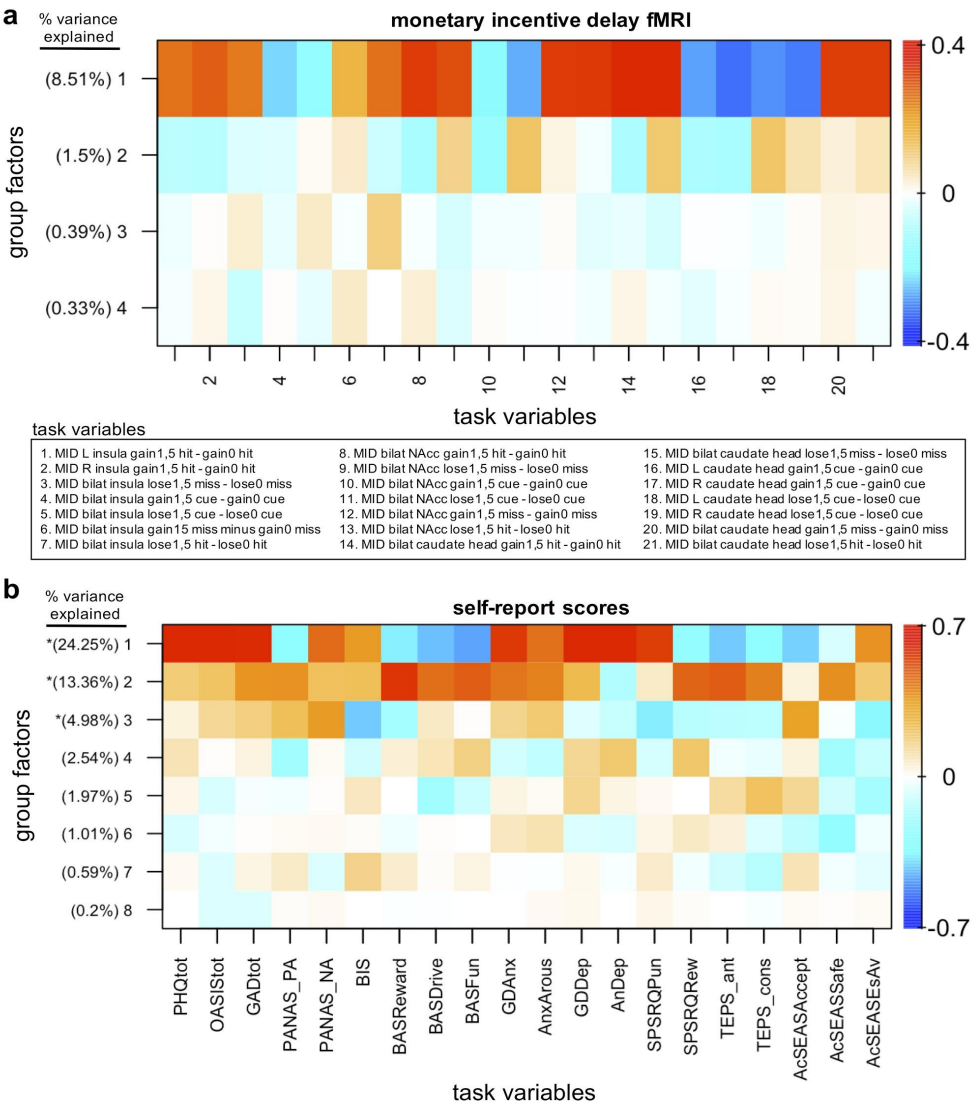


Figure S5. Within-task GFA loading heatmaps. (a) Factor loadings from the within-task monetary incentive delay (MID) GFA. fMRI contrast (x-axis) loadings whose 95% credible interval did not contain zero are shown in bold. (b) Factor loadings from the within-task self-report GFA. All self-report variables (x-axis) had at least one loading whose 95% credible interval did not contain zero. Heatmap colors indicate the weight of each variable loading. Robust latent factors are sorted in descending order by mean % variance explained. Asterisks indicate latent factors that contained at least one task variable loading whose 95% credible interval did not contain zero. MID: monetary incentive delay, NAcc: nucleus accumbens, PHQ: Patient Health Questionnaire, OASIS: Overall Anxiety Severity and Impairment Scale, GAD: Generalized Anxiety Disorder questionnaire, PANAS: Positive and Negative Affective Schedule, BIS/BAS: Behavioral Inhibition System and Behavioral Activation System questionnaire, SPSRQ: Sensitivity to Punishment and Sensitivity to Reward Questionnaire, TEPS: Temporal Experience of Pleasure Scale, AcSEAS: Acceptance, Safety, Escape/Avoidance Scale.

2.7. Correlational analysis of cross- and within-task group factors

To further examine the robustness of the GFs extracted from the cross-task analysis, we looked at the correlation structure between all cross- and within-task GF scores (Figure S6a). This analysis was therefore restricted to participants from the cross-task GFA (N=118). If a given cross-task factor is robust, it should also be identified when GFA input variables are restricted to a single task and the sample size is increased. Indeed, all cross-task GFs had a corresponding within-task GF with which it was correlated at a magnitude of at least 0.58 (Spearman's Rho), with 6 factors having correlation coefficient magnitudes greater than 0.95. (Figure S6b).

Correlation values tended to scale by variance explained within each task, such that cross-task GFs that explained the most variance tended to show the highest correlation coefficients with a corresponding within-task GF. For example, correlation coefficients between the first cross-task GF extracted for each of the fear conditioning, MTPT, and self-report blocks and the first GF extracted in the corresponding within-task GFA were all above 0.99 (Figure S6b). MID GFs are a notable exception to this trend, as the first and fourth cross-task MID factors (GF2_MID1 and GF11_MID4), while not strongly intercorrelated ($r = -0.01$, $p > 0.05$) both map onto the first within task MID GF (MID GF1) with more moderate correlation coefficients ($r = 0.59$, $p < 0.01$ and $r = 0.64$, $p < 0.01$, respectively). This suggests that the within-task MID GFA identified a single factor that could account for variance in the MID task that required two separate factors, accounting for separate portions of MID task variance, in the less-powered cross-task GFA. Cross-task factors also tended to be uniquely correlated with a given within-task factor, as can be seen from the sparse nature of the correlation matrix in Figure S6a, and the difference in the magnitudes

of the highest and second highest cross correlations with within-task factors observed for each cross-task factor (mean ± SD: 0.58 ± 0.24; Figure S6b).

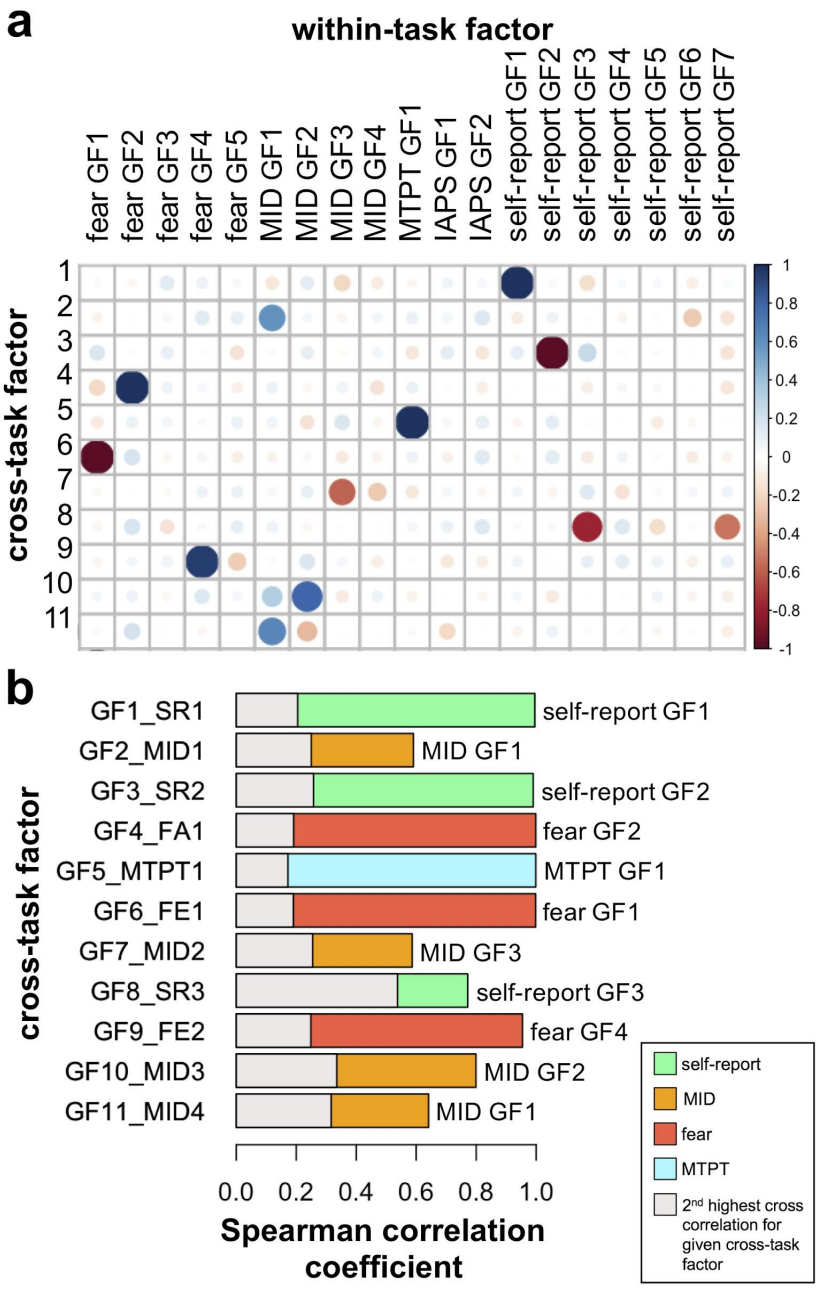


Figure S6. Spearman correlations between cross-task (main text Figure 1) and within-task factors (main text Figure 2, and supplemental Figure S5). (a) Spearman correlation matrix for all cross-task and within-task group factors. (b) Highest two absolute cross correlations with within-task

factors for each cross-task factor. The highest cross correlation for each cross-task factor is shown in color, with the corresponding within-task factor indicated to the right. The second highest cross correlation value is shown in gray (specific within-task factors not reported, but see panel a). MID: monetary incentive delay, MTPT: mirror tracing persistence task, IAPS: international affective picture system.

2.8. Regression models of relationships between within-task latent factors

We used linear regression to investigate potential relationships between latent variables derived from the within-task GFAs. Specifically, regressed within-task self-report factors scores on factor scores derived from the within-task GFAs for the fear conditioning, MID, IAPS, and MTPT tasks, including age, gender, education, and data collection site as covariates. To minimize the type 1 error rate and make this approach as meaningfully targeted as possible, we selected only the within-task self-report GFs that reflected significant valence processing according to our valence quantification analyses (see Results section of the main text). This process identified the two within-task self report factors that explained the most variance among the self-report variable block (SR1: valence score = -8.51, $p < 0.001$; SR2: valence score: 1.70, $p = 0.04$) as our dependent variables. This is consistent with correlational analyses showing that these two GFs map onto cross-task factors GF1_SR1 and GF3_SR2, respectively (Figure S6), which were also the only two cross-task self-report GFs that showed significant valence processing (Figure 3). As shown in Table S4, we found four significant predictors from all regression models (from a total of 24 comparisons across 8 models), all showing small effect sizes, as indexed by Cohen's $f^{2\,(38)}$; Table S4).

Table S4: Significant effects from within-task GFA regression analyses.

[see Tables at end of document]

*By convention, Cohen's f^2 effect sizes are categorized as follows: $f^2 > 0.02$, 0.15, and 0.35 for a small, medium, and large effect sizes, respectively.

2.9. Valence Quantification and Interpretation of Latent Factors

While the distribution of variable loadings can tell us whether a given GF is task-specific, it does not indicate the extent to which a given factor reflects positive or negative valence processing per se. We therefore sought to quantify the extent to which a given GF corresponds to positive and negative valence processing. Each variable loading for a given GF was assigned a valence coefficient of either +1 (arbitrarily assigned to variables posited to reflect positive valence, such as contrasts for monetary gains on the MID task) or -1 (assigned to variables posited to reflect negative valence, such as contrasts for monetary loss on the MID task). A valence score for each GF was then calculated by taking the sum of products of loading weights and their corresponding valence coefficients. Permutation tests were then used to compare the resulting valence scores with a permuted null distribution with shuffled valence coefficients (10,000 iterations). Significance was evaluated at alpha = 0.05, Bonferroni corrected for multiple comparisons. Because the permutation test relies on a relatively even distribution of variables with positive and negative valence coefficients, we restricted this analysis only to the MID and self-report variable blocks. For example, the fear conditioning GFA variables could not be meaningfully assessed by this analysis as contrasts between the CS+ and CS- would all have the same valence coefficient.

Valence quantification analyses revealed that the two GFs that explained the most variance within the self-report variable block of the cross-task GFA reflected valence processing (GF1_SR1: valence score = 8.09, $p < 0.001$; GF3_SR2: valence score = -2.05, $p < 0.01$; Figure S7a). Conversely, only the GF that explained the *least* variance within the MID block reflected valence processing (GF11_MID4: valence score = 1.45, $p = 0.04$; Figure S7b). These self-report and MID GFs explain a cumulative 12.22 % and 0.24% of the total variance among all GFA input variables,

respectively (Figure 1). Further, when valence coefficients for the MID block were reassigned so as to reflect the difference between fMRI contrasts corresponding to anticipation periods in the MID task (+1) and fMRI contrasts corresponding to consumption periods (-1), the GF that explained the most variance, and, again, the GF that explained the least variance were found to reflect this difference in task conditions (GF2_MID1: valence score = 3.54, $p < 0.01$; GF2_MID4: valence score = 2.37, $p < 0.001$, Figure S7c).

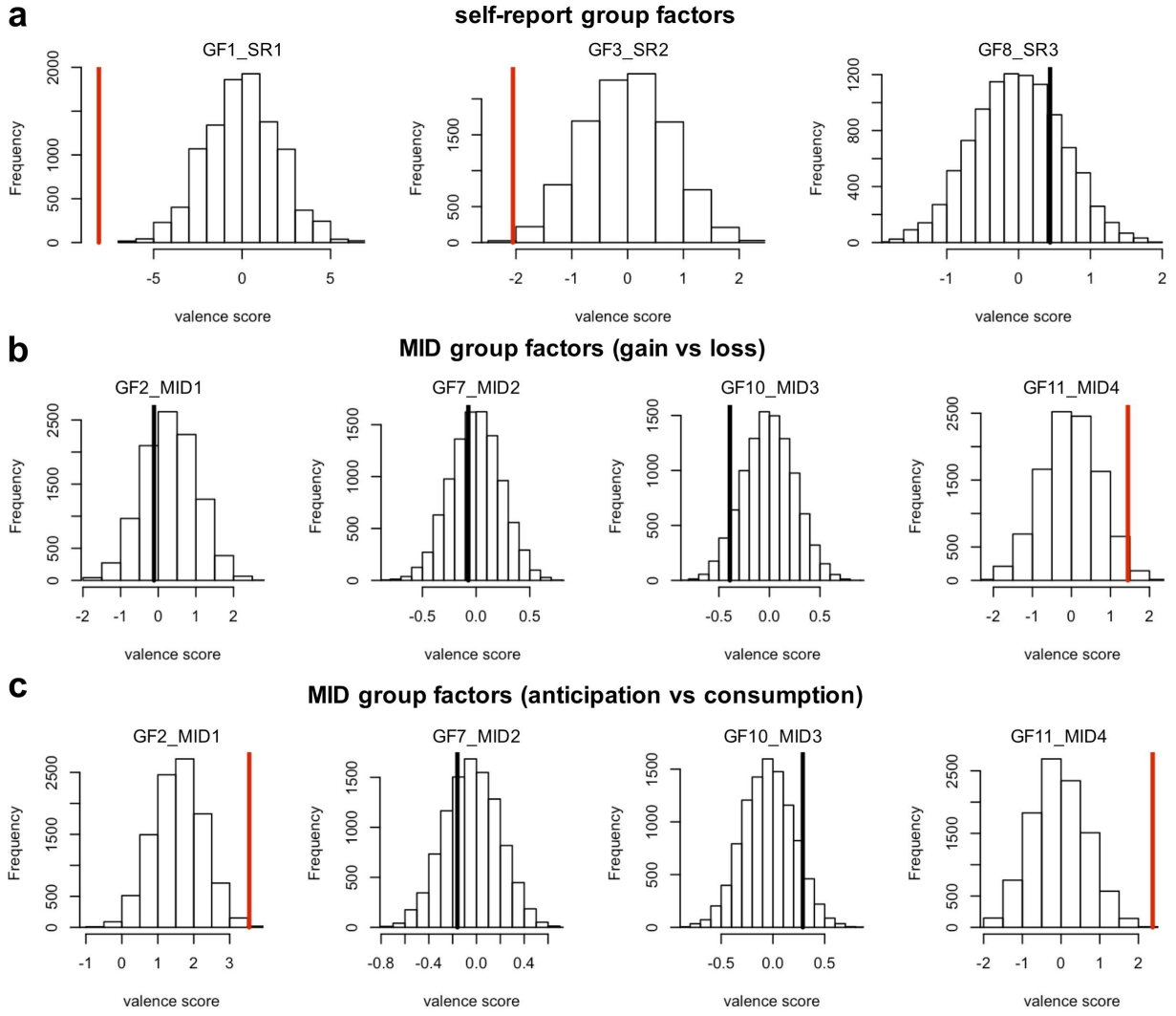


Figure S7. Valence quantification analysis. White bars indicate the null distribution of valence scores computed from 10,000 random permutations of valence coefficients. Observed valence scores for each group factor (GF) are indicated by black (not significant) or red (significant) bars. Significance was evaluated at a Bonferroni corrected alpha value of 0.0125. (a) Valence scores for the three cross-task GFs that loaded onto self-report questionnaire variables (GF1_SR1, GF3_SR2, and GF8_SR3). See Supplemental Methods for valence coefficient assignments (+1 or -1) to specific self-report variables. (b) Valence scores for the four cross-task GFs that loaded onto MID fMRI contrasts (GF2_MID1, GF7_MID2, GF10_MID3, GF11_MID4). Positive and negative valence coefficients were assigned to gain and loss contrasts, respectively. (c) Valence scores for the same four cross-task MID GFs from (b), but with positive and negative coefficients assigned to anticipation and consumption contrasts, respectively.

2.10. Split-half Reliability

We used Cronbach's coefficient α (39) and Guttman's λ6 (40) to examine the reliability of fMRI and physiological variables through the alpha function in R (Table S5). The reliability of valence, arousal, and contingency ratings could not be assessed because only single measures were collected for each of these variables. For the fMRI variables, we examined reliability across ROIs for a given fMRI contrast (e.g., CS+ minus CS- in the fear conditioning task, or anticipated gains minus anticipated losses in the MID task). MRI variables had split-half reliabilities (mean ± SD: $\alpha=0.86\pm0.12$, $\lambda6=0.89\pm0.07$) within a conventionally acceptable range (greater than 0.7), whereas physiological variables had reliabilities below this range ($\alpha=0.29\pm0.17$, $\lambda6=0.36\pm0.17$; Table S5).

Table S5: Split-half reliability of fMRI and IAPS physiological variables.
[see Tables at end of document]

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Supplemental Tables

Table S1: Number of variables and N of missing data.

	neuroimaging measures			**physiological measures**			**behavioral measures**			**subjective ratings**		
task	**variables**	**# of variables**	**# missing data**	**variables**	**# of variables**	**# missing data**	**variables**	**# of variables**	**# missing data**	**variables**	**# of variables**	**# missing data**
FA	ROI activations	9	48	-	-	-	contingency ratings	2	61	-	-	-
FE	ROI activations	8	52	-	-	-	contingency ratings	2	62	-	-	-
MID	ROI activations	21	48	-	-	-	-	-	-	-	-	-
MTPT	-	-	-	hear rate	2	47	task duration	1	39	-	-	-
IAPS	-	-	-	heart rate, SCR	3, 3	63,85	-	-	-	valence, arousal ratings	6	31
Self-report	-	-	-	-	-	-	-	-	-	self-report question-naires	20	5

Table S2: Sample Characteristics of subjects enrolled at each site

	UCSD = 100*		UCLA = 125*	
Characteristic	**Mean**	**SD**	**Mean**	**SD**
age (years)	32.9	11.5	29.6	10.9
education (years)	16.1	2.68	15.7	2.48
	N	**%**	**N**	**%**
gender (N,% female)	71	72.4	92	73.6
major depressive disorder (MDD)	54	54	54	43.9
generalized anxiety (GAD)	64	64	44	35.2
Ethnicity	**N**	**%**	**N**	**%**
Hispanic/Latino	17	17	27	21.6
Not Hispanic/Latino	81	81	95	76
Unknown/Decline to Respond	2	2	3	2.4
Race	**N**	**%**	**N**	**%**
Black/African-American	1	1.02	13	10.4
White/Caucasian	60	61.2	48	38.4
Asian/Asian-American	21	21.4	32	25.6
Native-American/Alaskan Native	1	1.02	1	0.8
Native-Hawaiian/Pacific Islander	0	0	1	0.8
Unknown/Decline to Respond	1	1.02	4	3.2
More than one race	8	8.16	14	11.2
Other	6	6.12	12	9.6
Relation Status	**N**	**%**	**N**	**%**
Single	32	32	69	55.2
Married	24	24	5	4
In a committed romantic relationship	28	28	32	25.6
Divorced/separated	7	7	16	12.8
Widowed	2	2	0	0
Other	4	4	0	0
Medication Status	**N**	**%**	**N**	**%**
SSRI Only	10	0.1	10	0.08
SNRI Only	1	0.01	1	0.01
Benzodiazepine only	7	0.07	1	0.01
SSRI + other	1	0.01	6	0.05
Benzodiazepine + other	0	0	1	0.01
SSRI + Benzodiazepine	1	0.01	1	0.01
Other	3	0.03	5	0.04
Unmedicated	77	0.77	100	0.8

**The total numbers of participants enrolled in the study from each site were 100 and 125 from UCSD and UCLA, respectively. Number of missing samples for demographic and diagnostic info is as follows: age, gender, race:* $N_{UCSD}=2$, $N_{UCLA}=0$; *education:* $N_{UCSD}=2$, $N_{UCLA}=3$; *MDD diagnoses:* $N_{UCSD}=0$, $N_{UCLA}=2$. *Note that while the characteristic data reported here are for all participants enrolled in the study (N=225), subsets of the data ranging from N=118 to N=180 were used for GFA*

Table S3: Symptom characteristics related to negative and positive valence systems.

	UCSD N = 98		UCLA N = 122	
	Mean	**SD**	**Mean**	**SD**
Negative valence system				
PHQ9	11.88	5.54	11.48	5.7
OASIS	9.52	3.51	9.68	3.84
PANAS negative	18.93	6.66	17.61	7.09
GAD7	10.88	5.09	9.48	4.81
MASQ General Distress	28.62	7.83	25.58	8.04
MASQ Anxious Arousal	31.7	10.97	28.65	8.83
MASQ Depressive	35.63	10.86	35.82	10.59
MASQ Anhedonic	74.53	14.82	76.33	13.43
BIS	24.17	3.63	23.86	3.3
SPSRQ punishment sensitivity	15.04	5.11	15.8	5.24
Positive valence system				
PANAS positive	23.69	7.92	21.47	7.12
BAS drive	10.69	2.99	10.3	2.84
BAS funseeking	11.29	2.67	10.92	3.16
BAS reward responsiveness	16.59	2.21	16.52	2.51
SPSRQ reward sensitivity	10.69	4.74	10.02	4.55
TEPS anticipatory pleasure	37.31	10.21	37.62	10.13
TEPS consumatory pleasure	33.92	7.98	33.17	9.03
AcSEAS Acceptance subscale	10.72	3.22	10.25	3.48
AcSEAS Safety Behavior subscale	10.13	2.21	9.83	2.41
AcSEAS Escape/Avoidance subscale	13.05	3.86	13.61	3.94

Table S4: Significant effects from within-task GFA regression analyses.

	Estimated β coefficient	*p* value	*Cohen's f^2
Fear-GF3 :: self-report-GF1	0.23	0.031	0.03
Fear-GF4 :: self-report-GF1	0.3	0.039	0.03
Fear-GF1 :: self-report-GF2	-0.15	0.040	0.03
MID-GF3 :: self-report-GF1	-1.69	0.010	0.04

*By convention, Cohen's f^2 effect sizes are categorized as follows: $f^2 > 0.02$, 0.15, and 0.35 for a small, medium, and large effect sizes, respectively.

Table S5: Split-half reliability of fMRI and IAPS physiological variables

			Standardized Cronbach's α	Guttman's Lambda 6 reliability	N variables	N subjects
Fear conditioning	FA		0.96	0.96	9	181
	FE		0.9	0.9	8	177
MID			0.73	0.82	21	182
IAPS	HR	positive	0.27	0.3	8	186
		negative	0.27	0.34	8	186
		neutral	0.05	0.08	8	186
	GSR	positive	0.28	0.43	8	147
		negative	0.57	0.61	8	147
		neutral	0.3	0.39	8	147