Severe Sexual Abuse Reduces Frontoparietal Network Activity during Model-Based
Reinforcement Learning Updates

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ABSTRACT

Trauma and trauma-related disorders are characterized by altered learning styles. Two learning processes that have been delineated using computational modeling are model-free and model-based reinforcement learning (RL), characterized by trial and error and goal-driven, rule-based learning, respectively. Prior research suggests that model-free RL is disrupted among individuals with a history of assaultive trauma and may contribute to altered fear responding. Currently, it is unclear whether model-based RL, which involves building abstract and nuanced representations of stimulus-outcome relationships to prospectively predict action-related outcomes, is also impaired among individuals who have experienced trauma. The present study sought to test the hypothesis of impaired model-based RL among adolescent females exposed to assaultive trauma. Participants (n=60) completed a three-arm bandit RL task during fMRI acquisition. Two computational models compared the degree to which each participant's task behavior fit the use of a model-free versus model-based RL strategy. Overall, a greater portion of participants' behavior was better captured by the model-based than model-free RL model. Although assaultive trauma did not predict learning strategy use, greater sexual abuse severity predicted less use of model-based compared to model-free RL. Additionally, severe sexual abuse predicted less left frontoparietal network encoding of model-based RL updates, which was not accounted for by PTSD. Given the significant impact that sexual trauma has on mental health and other aspects of functioning, it is plausible that altered model-based RL is an important route through which clinical impairment emerges.

INTRODUCTION

The pervasive, detrimental consequences of trauma are well-recognized, with a history of adverse experiences implicated in increased risk for poorer physical and psychological health outcomes, including depression, anxiety, substance use, autoimmune diseases, risky sexual behavior, and sleep disturbances [1-5]. Not only is the impact extensive, the direct and indirect costs of trauma are substantial, both in terms of financial costs for individuals and society for psychiatric and medical services, and in quality of life costs [6-7]. Because traumatic experiences have a broad impact on functioning, identifying mechanisms that contribute to impairment is a critical endeavor, as this may reveal key psychopathology prevention and intervention targets.

Trauma, particularly severe and/or chronic trauma, and trauma-related disorders are commonly associated with impairments in learning [8-9]. Aberrant learning can contribute to inflexible, maladaptive behavior, such as persistent avoidance, which is a hallmark symptom of posttraumatic stress disorder (PTSD) and a potent risk factor for the development of mental health disorders [10]. Increasingly, computational modeling is being applied in psychiatric research to quantify psychological processes, such as learning, with greater precision in an effort to delineate a mechanistic account of how these processes are disrupted among individuals with and at risk for psychopathology [11-12].

Two distinct learning processes that are well-characterized by computational modeling and highly applicable to trauma research are model-free reinforcement learning (RL) and model-based RL [13]. Whereas model-free RL utilizes information acquired via trial and error and is primarily implemented within the ventral striatum [14-15], model-based RL involves the development of cognitive maps that contain possible outcomes (i.e., mappings of context-dependent conditions) to prospectively make predictions about actions and is primarily

implemented via regions of the prefrontal cortex (PFC) and frontoparietal network (FPN), including dorsolateral prefrontal cortex (dlPFC) and inferior frontal gyrus, and regions of the parietal cortex, including the intraparietal sulcus (IPS) [14-17]. Broadly, regions of the PFC and FPN are implicated in abstract cognition and cognitive control processes [18-20], including sustained attention and updating working memory representations, which guide the pursuit of complex and goal-driven behaviors and are likely integral in the formation of model-based representations. Indeed, better performance on tasks that measure cognitive control (e.g., inhibitory control) predicts greater use of model-based versus model-free strategies during reinforcement learning [21].

Model-free RL aberrations have been identified among individuals with interpersonal violence-related PTSD [22-24]. For example, compared to adults without PTSD, women with PTSD exhibited reduced encoding of positive prediction errors (i.e., the occurrence of an unexpected reward) within a ventral striatum/medial PFC network during a RL task [24]. Among adolescents, a history of assaultive trauma predicted reduced encoding of negative prediction errors (i.e., the omission of an expected reward) within the salience network during a RL task [23]. Indicative of an impact of trauma exposure rather than PTSD per se on RL, reduced salience network encoding was not accounted for by PTSD diagnosis or symptom severity.

While altered model-free learning is one route through which learning is disrupted (e.g., fear and safety stimulus-outcome expectations), impaired model-based RL may be another pathway through which learning is disrupted. Critically, model-based RL disruptions may impair individuals' ability to effectively encode and predict abstract outcomes, plan future behavior, and navigate complex environments. At present, no prior studies have used computational modeling to identify the impact of trauma on model-based RL; thus, the degree to which trauma impacts

the formation of abstract model-based representations about one's environment and how to navigate it is unknown. Given that individuals with a history of trauma and PTSD exhibit difficulties integrating contextual information into fear and safety learning [25] and that trauma/PTSD predict atypical neural activity within brain regions that support model-based RL [26-27], it is anticipated that model-based RL processes are disrupted by a history of assaultive trauma.

The present study sought to build on previous research by using computational modeling to investigate the impact of assaultive trauma on model-based RL among adolescent females. Females were selected for the present study because they are more likely to be victims of assaultive trauma [28] and exhibit a greater lifetime risk of developing PTSD than males [29-30]. Adolescents were selected for inclusion given that the onset of psychopathology substantially increases during adolescence, especially among females [31-32], and among those who have experienced early trauma [33]. Thus, adolescence is a critical time period in which to assess the impact of trauma on learning processes.

It was hypothesized that a history of assaultive trauma would predict 1) less use of model-based relative to model-free RL. Further, it was hypothesized that, 2) compared to adolescents without a history of assault, a history of assaultive trauma would predict reduced model-based encoding within the frontoparietal network (FPN), including dlPFC and IPS. The FPN was of primary interest given that regions of this network are most commonly activated across model-based RL studies, suggesting that these regions are particularly instrumental in the implementation of model-based RL [15-16]. Consistent with dose-dependent relationships between trauma severity and health/mental health outcomes, it was hypothesized that 3) a dose-dependent relationship between trauma severity and impaired model-based RL would emerge.

Because there is evidence available that trauma types differentially affect some aspects of cognitive functioning [34-35], the unique impact of physical and sexual abuse on model-based RL was explored. Finally, based on previous research indicating that the impact of trauma on learning processes is not specific to PTSD [19], it was anticipated that 4) the relationship between trauma and model-based RL would not be accounted for by a diagnosis of PTSD.

MATERIALS AND METHODS

The present study constituted a secondary analysis of data that was published in Cisler et al. [23]. Sixty-two adolescent females between the ages of 11 and 17 with (n=30) and without (n=32) histories of directly experienced physical or sexual assault were recruited. Participants were recruited from and completed the study at two different sites (Little Rock, AR (n = 27) and Madison, WI (n=35), $\chi^2(1)=1.03$, $p=.310$).

Inclusion criteria for control participants included no history of trauma exposure, current psychiatric disorders, current psychotropic medication usage, or psychiatric treatment. Inclusion criteria for assaulted participants included a history of directly experiencing physical or sexual assault, and these participants were recruited such that approximately half of the assaulted sample had a PTSD diagnosis. Exclusionary criteria included current major medical disorders, developmental disorders, neurocognitive disorders, history of psychotic symptoms, history of traumatic brain injury, contraindications for magnetic resonance imaging, loss of consciousness lasting more than 10 minutes, and pregnancy. Two participants (one control and one participant with a history of assaultive trauma) were excluded from all analyses due to 1) psychiatric medication use and 2) extreme head motion, yielding a final sample of sixty participants. For full study methods, see Cisler et al. [23]. The final sample consisted of 29 controls and 31

adolescents exposed to assault (n=17 with a current diagnosis of PTSD; see Table 1 for demographic and clinical characteristics).

Clinical Interviews and Measures

The Clinician-Administered PTSD Scale, Child and Adolescent Version was used to assess symptoms of PTSD symptoms [36]. The Mini-International Neuropsychiatric Interview for Children and Adolescents was administered to assess for current and lifetime mental health disorders. Participants completed the short-form version of Childhood Trauma Questionnaire (CTQ), which is a self-reported measure that assesses for physical abuse, sexual abuse, emotional abuse, physical neglect, and emotional neglect [37-38]. The CTQ can be used as a dimensional and/or categorical assessment of childhood maltreatment. Intelligence quotient was assessed using the One-Word Receptive Picture Vocabulary Test, Fourth Edition [39-40].

Three-Arm Bandit Task

Participants completed two versions of a three-arm bandit task, one of which included faces (“social task”) and another which included houses (“neutral task”). Given that the primary goal of the present study was to examine the relationship between assaultive trauma and model-based RL, to ensure that the tasks elicited model-based RL, behavioral results from each task were fit to a model-free and model-based RL model (see below) prior to implementing the primary analyses. Because Cisler et al. [23] found that the impact of assault severity on RL-related encoding was more robust in the social than the neutral task, possibly reflecting differential engagement of learning processes by these tasks, it was anticipated that the social task would elicit model-based RL to a greater extent than the neutral task. Results indicated that learning strategy use during the neutral task was well-captured by a model-free RL approach (see the Supplement). In contrast, the social task was better captured by a model-based than model-

free approach (see below), and was therefore selected for modeling. The social task consisted of 90 trials in which participants were presented with the faces of three individuals with a neutral expression (Supplemental Figure S1). Participants were asked to invest \$10 in one of the individuals, each of whom had a different likelihood (80%, 50%, or 20%) of returning a reward of \$20 (vs. \$0). The probabilities of reward associated with each face switched every 30 trials. Each trial consisted of a decision, anticipation, and feedback phase. The primary trial phase of interest in the present study was the feedback phase, during which the outcome (reward vs. no reward) was delivered.

Computational Modeling

A risk-sensitive anticorrelated Rescorla-Wagner (RW) model, identified as the best-fitting model in Cisler et al. [23], was used to investigate model-free RL [41]. The standard RW model updates parameters from trial to trial as follows: $V_{t+1,c} = V_{t,c} + \alpha \times \delta_t$, where t is the current trial, $V_{t,c}$ is the current associative strength, δ_t is the current prediction error (PE; $outcome_t - V_{t,c}$), α is the learning rate, and c is the current selected option. On a given trial, the current associative strength ($V_{t,c}$) between an option c and an outcome predicts choice behavior, and the discrepancy between the outcome and expected outcome leads to a PE. The associative strength and PE then update the associative strength on the following trial ($V_{t+1,c}$; see Supplemental Figure S2). The risk-sensitive anticorrelated version of the RW model updates associative strengths for unselected options (e.g., options d and e) in the direction that is opposite of the PE for the selected option and uses a separate learning rate for positive and negative outcomes. To capture individual differences in exploration and exploitation (i.e., the tendency to try new options or to keep selecting an option that is rewarding, respectively) that impact action likelihood, associative

strengths were transformed using a softmax parameter. Additional RW model information is included in the Supplement.

For model-based RL, a latent state (LS) learning model was used [42]. LS learning involves learning multiple associations between options and outcomes and inferring which association to use at each point in the task. A latent state is a set of associations that specify what a learner should expect from selecting any option and is conceptualized as a set of abstract task rules/hypotheses. In aggregate, latent states describe multiple sets of task rules/hypotheses that define an entire task. To capture multiple associations, the LS model indexes associative strengths by an integer l (the latent state), with current associative strength of option c for latent state l ($V_{t,c,l}$). The LS model also captures the degree to which individuals believe that current conditions reflect a given latent state (i.e., latent-state beliefs), denoted by $p_{t,l}$.

Beliefs and associative strengths are iteratively updated based on PEs specific to each latent state (see Supplemental Figure S2). Beliefs are updated according to an approximate Bayes rule based on PEs and measure the magnitude of changes in latent-state beliefs on a trial by trial basis (*delta* beliefs, dB). That is, dB on a trial reflects the degree to which individuals update internal models after observing the outcome on that trial. Thus, larger updates reflect greater changes in latent-state beliefs (i.e., beliefs about current task rules/hypotheses). Behavior on the following trial is predicted by associative strengths weighted over latent states based on prior latent-state beliefs: e.g., for option c , $V_{t,c} = \sum_l p_{t,l} V_{t,c,l}$. Individual differences in exploration and exploitation were captured by transforming associative strengths ($V_{t,c}$) using a softmax parameter. The following parameters derived from the LS model were used in the present study: trial-by-trial $V_{t,c}$, PE δ_t , and dB.

The RW and LS models were fit to each participant's behavior using maximum likelihood estimation and resulting log likelihoods were used to calculate Akaike information criterion (AIC) to compare fit between the two models, with lower AIC values reflecting better fit. The difference between LS and RW model fit (*delta* AIC, dAIC) was calculated for each participant by subtracting RW AIC from LS AIC, with lower values reflecting relatively greater use of LS versus RW learning strategies for the task.

The impact of trauma on learning strategy use was tested with a linear regression model: dAIC was regressed onto variables reflecting the contrast of controls versus assaultive trauma (controls = -1, trauma = 1), with age, IQ, and study site included as covariates. Separate linear models tested the impact of CTQ Total Severity and the CTQ assault-related subscales (Physical and Sexual Abuse) using identical covariates. To rule out the impact of PTSD, follow-up analyses included PTSD diagnostic status (controls and assaulted without PTSD = 0, PTSD = 1). Linear regressions were carried out with MATLAB (fitlm; The MathWorks, Inc., Natick, MA).

Neuroimaging

Acquisition and preprocessing information are provided in the Supplement. Neuroimaging data was excluded from three participants due to head motion and malfunction with the head coil, yielding a sample of fifty-seven participants for neuroimaging analyses. All neuroimaging analyses focused on the LS model (see Behavioral Results section below).

Voxelwise analyses.

For within-subject analyses, each participant's voxelwise time courses were regressed onto the design matrix using AFNI (3dREML) [43]. The design matrix included the anticipation, decision, and outcome phases of the task. The anticipation and decision phases were parametrically modulated by trial-by-trial associative strength ($V_{t,c}$) from the LS model, and the

outcome phase was parametrically modulated by trial-by-trial PE (δ_t) and dB from the LS model. The beta coefficients for the outcome phase modulated by dBs, which characterized model-based RL updates, were carried forward to second-level analyses. In parallel to the behavioral analyses, linear mixed-effects (LME) models tested the effect of trauma (again using effect coded variables) on dB, controlling for age, IQ, and study site. Based on behavioral analyses where sexual abuse was uniquely associated with learning strategy (see below), only CTQ Sexual Abuse severity scores were entered as predictors of dB encoding. LMEs were implemented using MATLAB (fitlme; The MathWorks, Inc., Natick, MA).

Independent Component Analysis.

An independent component analysis (ICA) identified spatially distributed neural networks of temporally coactivated voxels [23]. Thirty-five components were identified, 16 of which were functional networks that included a left and right FPN that were of primary interest. In addition to the FPNs, follow-up analyses were implemented with eight networks that have been identified within previous trauma or PTSD research (see Supplemental Figure S7). Within-subject analyses were identical to the voxelwise analyses and implemented in MATLAB. Second-level analyses were also identical to the voxelwise analyses. For the primary analyses, Bonferroni correction was applied for the two FPN networks ($p < .025$) and the post-hoc analyses across all networks were corrected for eight networks ($p < .006$).

RESULTS

Behavioral Results

Performance, based on number of rewarded trials, was above chance (i.e., 33%; $M = 58\%$, $SD = 8\%$). Across participants, the LS model yielded a lower AIC value than the RW model (128.56 vs. 133.12). Although the mean difference in AIC fit was non-significant ($t(59) =$

1.78, $p = .080$), based on AIC, the LS model provided a better fit for a greater proportion of participants than the RW model ($n = 38$ vs. $n = 22$, $\chi^2(1) = 4.27$, $p = .040$; see Figure 1A). Mean trial-by-trial dBs were calculated across participants to examine whether changes in the dB updates followed the changes in the task. Supporting the validity of the LS model, which purports that changes in task conditions lead to revisions in latent-state beliefs (i.e., the presence of different context/rules), the largest changes in latent-state beliefs followed switches in task rules (every 30 trials), which prompted model updates of task representations (see Figure 1B).

Trauma exposure did not predict dAIC ($t(55) = 1.49$, $p = .141$). Furthermore, neither CTQ Total nor Physical Abuse (PA) severity predicted dAIC (CTQ Total: $t(55) = 1.85$, $p = .070$; CTQ PA: $t(55) = 1.17$, $p = .247$). By contrast, greater levels of CTQ Sexual Abuse (SA) predicted higher dAIC values ($t(55) = 3.12$, $p = .003$). Despite the emergence of a linear relationship between CTQ SA severity and dAIC, the scatter plot of this relationship indicated that this effect was driven by individuals with severe SA (see Supplemental Figure S3). To confirm this, post-hoc tests were utilized to assess for a non-linear association between model-based RL and SA. To this end, categorical CTQ SA groupings were created following established cutoff scores [37]. Participants with no (CTQ SA < 6) and low-to-moderate (CTQ SA ≥ 6 and < 13) SA scores ($n=49$) were compared to participants with severe (CTQ SA ≥ 13) SA scores ($n=11$). Task performance was poorer among those with severe SA than those with no-to-moderate SA ($M = 60\%$ vs. $M = 52\%$, $t(55) = -2.37$, $p = .022$). As shown in Figure 2A, the LS model provided a better fit for a greater proportion of participants with no-to-moderate SA than those with severe SA (71% vs. 27%, $\chi^2(1) = 7.54$, $p = .006$). Additionally, Figure 2B shows that adolescents with a history of severe SA had higher dAIC values relative to adolescents with no-

to-moderate SA ($t(55) = 3.10, p = .003$). The impact of severe versus no-to-moderate SA on dAIC held after controlling for a diagnosis of PTSD ($t(54) = 2.42, p = .019$).

Neuroimaging

Voxelwise Analyses.

There were no main effects of dB updating on neural activity and there were no modulatory effects of dAIC on dB updating. There was no evidence of differences in dB updating among adolescents with a history of trauma relative to controls. Because only CTQ SA severity predicted RL strategy, only this CTQ subscale was included in the neuroimaging analyses. No significant effects emerged for SA (scalar or coded based on severity).

Independent Component Analysis.

A main effect of dB encoding was evident within the right $t(50) = 3.11, p = .003$, but not left ($t(50) = -1.14, p = .260$), FPN. Although higher dAIC values predicted lower activity within the left FPN ($t(49) = -2.17, p = .035$), this did not survive Bonferroni correction ($p < .025$). There was no significant effect of assaultive trauma on left ($t(49) = -1.29, p = .204$) or right FPN ($t(49) = -1.94, p = .059$) activity relative to controls (see Supplemental Table S1 and Figure S5). There was a scalar relationship between SA and dB encoding in the left FPN ($t(49) = -2.30, p = .026$), which did not survive Bonferroni correction. In parallel with the behavioral analyses, when SA was coded based on severity, there was evidence of reduced dB encoding in the left FPN among adolescents with severe versus no-to-moderate SA ($t(49) = -2.73, p = .009$; see Figures 3A and 3B). The effect of severe versus no-to-moderate SA on left FPN was not accounted for by PTSD diagnosis ($t(48) = 2.18, p = .034$). Results of analyses with other networks for severe versus no-to-moderate SA are provided in the Supplement (see Supplemental Table S2 and Figure S6).

Ruling Out Additional Confounds

Analyses that rule out the effects of additional confounds (psychotropic medication use, anxiety symptoms, depressive symptoms) on results are included in the Supplement (see Supplemental Table S3). Only one result was no longer significant after accounting for covariates. Specifically, the impact of severe SA on performance became marginally non-significant after including anxiety symptoms ($t(54) = 1.86, p = .068$).

DISCUSSION

The present study examined the impact of trauma on model-based RL. Whereas neither an overall effect of general assaultive trauma exposure nor a linear dose-dependent impact of general assaultive trauma exposure on model-based RL emerged, exposure to severe sexual abuse predicted impaired model-based RL. Computational modeling revealed that although more participants used a model-based than model-free approach during the social learning task, the majority of participants with a history of severe sexual abuse used a model-free strategy. Suggestive of model-free RL being a less effective strategy, task performance was generally poorer among adolescents with severe versus no-to-moderate sexual abuse. In addition to predicting less use of model-based relative to model-free RL, severe sexual abuse predicted reduced FPN encoding of trial-by-trial updates in latent-state beliefs. As hypothesized, effects of sexual abuse were not accounted for by a diagnosis of PTSD.

According to results, early sexual abuse appears to have a detrimental effect on cognitive processes that support model-based RL. Childhood sexual abuse is associated with impairment in multiple domains of cognitive functioning in children and adolescents that are not fully accounted for by PTSD, including executive function (EF) processes [44]. Executive function impairment among individuals with a history of sexual abuse is not only evident in childhood and adolescence, but in adulthood as well and across multiple EF domains, including inhibition,

updating working memory, and shifting [34, 45]. Notably, there is substantial overlap among brain regions/networks that implement EF processes (e.g., FPN, lateral PFC, dlPFC, IFG) [46-47], and those that support model-based RL (e.g., FPN, lateral PFC, dlPFC) [14-17].

One way that early sexual abuse may impair cognitive processes that support model-based RL is via disruption of the foundational development of the FPN. The function and anatomical structure of regions that comprise the FPN are particularly vulnerable to the effects of early stress [48-50], given the protracted maturational time course of the PFC [51]. While the general structure of the PFC is reached by early adolescence, changes in myelination, synaptogenesis, and synaptic pruning continue into the early to mid-twenties [52]. Sexual abuse is associated with higher rates of shame, experiential avoidance, and self-blame than other forms of abuse, suggesting that this form of abuse may have particularly detrimental effects on cognitive and psychological processes [53]. Indeed, early sexual abuse uniquely predicts important outcomes, such as language ability, memory performance, and risk for mental health outcomes, including anxiety disorders, substance dependence, and suicide attempts, beyond other forms of abuse [54-55].

There are several limitations of the present study. First, the study was limited to adolescent females, which impacts its generalizability to males and individuals of other ages. Additionally, participants were recruited based on a history of assaultive trauma, and therefore results may underestimate the cumulative impact of trauma (i.e., total severity on the CTQ) on model-based RL. While not a limitation per se, it is important that a developmental perspective be considered regarding the results, as structures that comprise the FPN are still developing during adolescence. Whereas adolescents exhibit greater model-based RL than children (who almost exclusively rely on model-free RL), model-based RL use is strongest among adults [56].

Overall, results indicate that female adolescents with severe levels of sexual abuse engage in greater use of trial-and-error (model-free) learning compared to learning that involves building a complex cognitive map of the environment (model-based). It is notable that model-based RL deficits were evident in the present study during reward learning, as opposed to threat/punishment learning. This suggests that model-based RL deficits are potentially a general impairment and not specific to a threat processing context. Broadly, difficulty abstracting information and/or updating the cognitive maps that are used to predict outcomes as a result of impaired model-based RL could lead to difficulty navigating complex and shifting social environments that could in turn lead to decreased opportunities for social support, which is an important predictor of stress responsivity and mental health [57]. Additionally, difficulties identifying contextual factors indicative of social or predatory threat could potentially increase risk for revictimization, which is common among individuals with a history of trauma/sexual abuse [58-60]. Given the importance of model-based RL for general learning, RL deficits may also impact academic and work performance. In the future it will be important to further examine the impact of trauma, especially sexual trauma, on model-based RL.

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Tables

Table 1. Participants' Demographic and Clinical Characteristics.

	Control Group	Assaultive Trauma Group
n	29	31
Age , Mean (SD)	14.8 (2.3)	15.7 (1.5)
Race/Ethnicity (%)		
White	62	55
Black/African American	21	19
Asian	3	0
Hispanic, Latina	0	0
Pacific Islander	0	16
Native American	0	0
Other	14	10
IQ , Mean (SD)	116.9 (21.6)	101.2 (17.9)
CAPS Total Severity , Mean (SD)	n/a	44.4 (30.4)
CAPS Current # Symptoms	n/a	6.9 (5.4)
PTSD Diagnosis (%)	n/a	55
CTQ Total , Mean (SD)	29.6 (5.0)	50.8 (17.0) ^a
CTQ Physical Assault , Mean (SD)	5.7 (1.2)	8.2 (2.7) ^a
CTQ Sexual Assault , Mean (SD)	5 (0)	11.1 (6.9) ^a
CBCL Anxiety , Mean (SD)	2.4 (2.2)	8.3 (6.3) ^a
CBCL Depression , Mean (SD)	1.5 (1.9)	4.9 (3.2) ^a
Psychiatric Medications (%)	0	55
*IQ=Intelligence Quotient, One-Word Receptive Vocabulary Test; CAPS=Clinician-Administered PTSD Scale, Child and Adolescent Version; CTQ=Childhood Trauma Questionnaire; CBCL=Child Behavior Checklist; ^a p<.05		

Figures

Figure 1. A) A greater proportion of participants' behavior is better captured by the latent state (63%) versus the risk-sensitive anticorrelated Rescorla-Wagner (37%) model based on a comparison of each participants' LS versus RW Akaike information criterion (AIC) values. B) Trial by trial latent-state belief updates (delta beliefs) averaged across participants (blue line). The task's reward structure, which changes every 30 trials, is represented by the dashed line (e.g., the likelihood of receiving a reward after selecting cue A is 80% during the first 30 trials, 20% during the second 30 trials and 80% during the last 30 trials).

Figure 2. A) The behavior of a greater portion of participants' with no-to-moderate (71%) versus severe (27%) Childhood Trauma Questionnaire (CTQ) Sexual Abuse is better captured by the latent state versus the risk-sensitive anticorrelated Rescorla-Wagner model based on a comparison of each participants' LS versus RW Akaike information criterion (AIC) values. B) The difference in LS and RW AIC values (dAIC) is higher (higher dAIC values reflect poorer LS relative to RW model fit) among adolescents with severe versus no-to-moderate CTQ Sexual Abuse scores. (Note: the no and low-to-moderate groups are separated for visualization).

Figure 3. A) Spatial map of the left frontoparietal network (FPN) identified via independent component analysis (radiological convention). B) Left FPN encoding (regression coefficients from the first-level time-course modeling) decreases during changes in latent-state beliefs (delta beliefs) among adolescents with severe versus no-to-moderate CTQ Sexual Abuse scores. (Note: the no and low-to-moderate groups are separated for visualization).