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Research Article

Drift-Diffusion Modeling of Attentional Shifting During Frustration: Associations With State Frustration and Trait Irritability

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Irritability, a prevalent and impairing symptom in many mood and anxiety disorders, is characterized by aberrant responses to frustrative nonreward. Past research investigating irritability have used a cued-attention task with rigged feedback, the affective Posner task (AP), to induce frustrative nonreward. Previous studies have not been successful in linking differences in self-reported irritability to traditional AP metrics (i.e., reaction time and accuracy). Computational modeling, via the estimation of parameters reflecting latent cognitive processes, may provide insight into the cognitive mechanisms of irritability and reveal potential targets for mechanism-based interventions. This study applied the drift-diffusion model (DDM) to the AP to determine if DDM parameters are associated with individual differences in irritability. Young adults ($N = 152$, $M_{\text{age}} = 20.93 \pm 1.98$) completed the AP and self-reported state frustration and trait irritability. Multiple linear regressions were used to evaluate whether DDM parameters better predict state frustration and trait irritability over traditional AP metrics. Higher state frustration was predicted by lower decision threshold during the frustration block and larger decrease in this parameter between nonfrustration and frustration blocks, over traditional AP metrics. These findings demonstrate the potential of applying the DDM to study frustrative nonreward in healthy adult populations. The utility of DDM awaits validation in populations with clinical levels of irritability.

Keywords: drift-diffusion model; frustration; frustrative nonreward; irritability; reward

1. Introduction

Irritability, defined as an increased proneness to experience anger and frustration relative to peers [1], is a clinically significant symptom that cuts across many *externalizing* and *internalizing* disorders [2]. Irritability is associated with poor outcomes in children, including high rates of hospitalization, service use, and school suspensions [3, 4]. Irritability continues to predict poor outcomes into adulthood, including anxiety and depressive disorders [5–7], high suicidality [8–11], and low income and educational attainment, even after controlling for previous levels of irritability and adult psychiatric diagnoses [6]. However, research on the cognitive mechanisms of irritability in adults is relatively limited [12] and has focused on domains such as face emotion processing [12–14] rather than reward processing [15].

Irritability is conceptualized as aberrant behavioral and emotional responses to frustrative nonreward [1], defined as the psychological state induced by the failure to receive an expected reward [16]. Irritability may reflect individual differences in the frequency and intensity with which frustration is experienced [17, 18]. Indeed, the central role of frustration in the clinical presentation of childhood irritability is empirically supported [19, 20]. Thus, past research has used paradigms evoking frustration (i.e., through manipulating task difficulty or providing subjects rigged feedback) to study irritability-related pathophysiology [15, 21–24]. One commonly used paradigm is the affective Posner task (AP)—a cued-attention task with rigged feedback to induce frustrative nonreward and assess attentional shifting during frustration [15, 21–23]. In this task, participants are asked to identify the location of a target (left or right) following a cue by button press. The AP is composed of valid trials (i.e., the cue and target appeared in the same location) and invalid trials (i.e., the target appeared in the opposite location of the cue). The AP consists of a nonfrustrating condition during which participants win or lose money based on choosing the correct target and a frustrating condition that includes many (60%) rigged feedback (i.e., participants lose money regardless of their actual performance). The AP has been useful for investigating the neural correlates of frustration and their associations with irritability using both functional magnetic resonance imaging [21, 23] and electrophysiological measures (e.g., event-related potentials [ERP] [15]). Studies have found that, in response to rigged feedback (i.e., frustrating stimuli), irritability was associated with decreased amygdala and striatal responses in children [21], and with smaller feedback-related negativity (FRN) (i.e., an ERP indexing feedback sensitivity) amplitudes in young adults [15]. Conversely, a larger FRN following rigged feedback was related to greater emotion dysregulation in adolescents with a diagnosis of autism spectrum disorder [25]. During attention orienting following frustration, irritability was linked to increased frontostriatal activity in youth [23], suggesting greater prefrontal cortex engagement is needed to facilitate postfrustration adjustment and meet attentional demands during the AP.

Research examining the behavioral performance in the AP has largely relied on the use of the average response time (RT) and accuracy in task conditions (i.e., nonfrustration and frustration blocks). Past studies using these metrics revealed no association between self-reported continuous *trait* measure of irritability and RT or accuracy in the AP in children [22, 23] and adult [15] samples. Past studies conducting group comparisons showed that children with severe mood dysregulation (SMD) (a disorder characterized by severe, chronic, and impairing levels of irritability) had slower RT during frustration blocks, specifically on invalid trials, in the AP than healthy comparison children [21, 26]. Higher *state* measure of frustration was correlated with decreased RT during frustration runs in children [22], but this correlation was not found in adults [15]. However, multiple factors influence how quickly and accurately individuals respond on these types of tasks. Computational process models, such as the drift-diffusion model (DDM), capture the intraindividual variability across experimental trials and provide additional information about underlying cognitive mechanisms of decision-making [27–29]. Computational models may provide insight into associations between AP performance and trait irritability or state frustration. While there has been growing interest in the use of computational modeling to decompose cognitive processes involved in task-based behavior [30], research has yet to apply computational models to the AP. In the current study, we applied the DDM to the AP to evaluate whether this more nuanced approach can uncover linkages between DDM parameters and individual differences in self-reported trait irritability and state frustration.

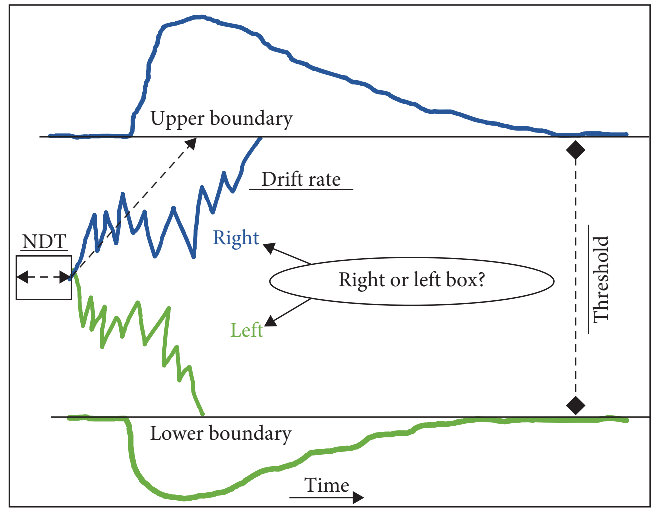

Figure 1: Simulated trajectories of the two drift processes (blue and green lines). *Note:* Evidence is noisily accumulated over time (x-axis) where the (average) drift rate continues until it reaches one of two boundaries, with a degree of separation defined by threshold (a), and a response is initiated. Upper (blue) and lower (green) panels refer to density plots for the two responses. The dashed horizonal line in the beginning of the drift processes indicates the non-decision time (NDT) where no accumulation happens. The dashed vertical line indicates the decision threshold, which governs boundary separation and, therefore, the amount of evidence required to make a decision. While simulation data are depicted here, hierarchical drift-diffusion modeling (HDDM) uses a closed-form likelihood function.

The DDM is an evidence accumulation model comprised of a class of algorithms used to jointly predict participants' RTs and decisions during binary decision making [27, 31]. The DDM assumes that between the time when an individual sees a stimulus and makes a binary decision, evidence is accumulating toward one of the two decisions (called thresholds). The point at which one of the thresholds is reached reflects the moment the individual decides. In the case of the AP, the thresholds reflect the participant's decision that the target appeared in the left or right location. The time required to make the decision (i.e., reach threshold) reflects four latent cognitive processes captured by DDM models: (1) the amount of accumulated evidence required to make a response (decision threshold); (2) non-decision-making processes like orienting gaze to the stimulus, perceptual encoding, and executing the motor response (non-decision time); (3) the relative starting point of the evidence accumulation process reflecting a possible tendency to make one decision over another (bias); and (4) information processing efficiency (drift rate; Figure 1). These latent variables, in turn, may vary across the different conditions of the AP and between individuals with varying irritability, making this model an ideal one with which to understand associations between irritability and AP performance.

Two of these parameters, decision threshold and drift rate, are of particular interest for the study of irritability and have drawn considerable attention in the cognitive literature [32]. The decision threshold parameter reflects the amount of information needed to make a decision between both the upper (e.g., responding "right") and lower (e.g., responding "left") boundaries. The decision threshold parameter for each person is thought to reflect the person's speed–accuracy tradeoffs, such that smaller values reflect a tendency to make faster but less accurate decisions, while larger decision threshold values indicate a tendency toward a more conservative or cautious decision-making style [33]. In addition, the frustration and nonfrustration blocks of the AP may lead to changes in decision thresholds that may be related to state frustration and trait irritability. Specifically, participants may shift toward an impulsive style of decision-making (preferring speed over accuracy) when frustrated, which would be reflected by decreases in decision threshold values in the frustration block (relative to the nonfrustration block).

The drift rate reflects the efficiency, or speed, with which an individual accumulates evidence across trials (and between task blocks) before making a decision (i.e., reaching threshold). Difficult trials or task conditions are notorious for negatively affecting processing efficiency (i.e., lower drift rate values [34]). As such, the drift rate has proven useful in finding intra- and interindividual differences on performance in conflict tasks such as the go/no-go task [35], flanker [36], antisaccade [37], and the continuous performance task [38]. In terms of the AP, drift rate may be influenced by the difficulty present in the different trial types [39–41], leading participants to be less efficient at processing and decreasing drift rate values during invalid, relative to valid, trials.

The AP may also impact the non-decision time parameter which reflects the time required to orient attention, encode the stimulus, and execute the motor response. Specifically, the frustration induction's emphasis on fast and accurate responding may reduce the amount of time spent orienting attention and accelerate the participants' motor responses, leading to reduced non-decision time parameter values during frustration. Indeed, speed–accuracy manipulations result in the expected effect on the decision threshold parameter but also impacts non-decision time (i.e., larger non-decision time estimates in the accuracy versus speed manipulations) [33, 42]. In addition, some participants (e.g., those with high trait irritability and/or state frustration) may be more likely to adjust these non-decisional processes during frustration, resulting in different non-decision time values under frustration (relative to nonfrustration).

Here, we leveraged a drift-diffusion framework to model AP performance in a sample of young adults. Given that computational models generate parameter estimates reflecting the latent cognitive processes driving differences in RT and performance between task conditions, this method holds strong promise in potentially relating AP performance and individual differences in irritability. The current study also seeks to explore associations between AP performance and *state frustration* given that prior studies have focused on associations between performance and *trait irritability* and/or diagnostic differences [22]. Frustration is defined as the emotional and behavioral response to blocked goal attainment [21] and the intensity of this response and may have unique associations with AP performance [22]. This research has the potential to guide future research utilizing frustration tasks to better predict individual differences in psychopathology. We hypothesized that in the AP, (1) the drift rate would be lower, reflecting decreased processing efficiency for invalid trials as compared to valid trials, and (2) the decision threshold parameter would be lower during the frustration as compared to the nonfrustration blocks, reflecting a shift toward an impulsive style of decision-making (preferring speed over accuracy) when frustrated. Importantly, we posit that the drift rate and threshold parameters of this model will be significantly associated with state frustration as well as trait irritability above and beyond simple RT and accuracy metrics.

2. Method

2.1. Participants. The total sample consisted of 154 young adults (ages 18–25 years, $M_{age} = 20.94$, $SD = 1.98$, 75.8% females) and was obtained by merging the two samples described. The AP was collected along with an EEG recording. Only the behavioral task data were analyzed and reported here. EEG and behavioral data of Sample 2 have been previously published [15]. Two participants were removed because their performance on the AP was associated with low convergence after model fitting (i.e., Gelman–Rubin statistic >1.1), suggesting unreliable performance (e.g., random responding and not engaging in the task). Thus, a final sample of 152 young adults ($M_{age} = 20.93$, $SD = 1.98$, 75.2% females) was used for our analyses.

2.1.1. Sample 1. Sample 1 consisted of 91 young adults (ages 18–25 years, $M_{age} = 21.37$, $SD = 2.27$, 61.1% females) recruited in 2022 through flyers in New Haven, Connecticut (USA). An initial phone survey determined eligibility: 18–25 years old, no major medical illnesses, no psychiatric condition other than depression, anxiety or ADHD, no substance abuse during the prior month, and no loss of consciousness >5 min. Participants were paid $15/h and were informed that they could earn an additional $25 during the AP. The majority (74.4%) of the sample was students. Most participants reported a family annual income of over $100,000 (46.2%), followed by $50,000 to $74,999 (19.80%), $75,000 to $99,999 (11.0%), $25,000 to $49,999 (8.79%), $15,000 to $24,999 (4.40%), and less than $14,999 (6.59%); 3.22% declined to answer. Participants predominantly identified as White/Caucasian (62.2%), followed by Asian (20%), Hispanic/Latin (17.8%), Black/African American (8.9%), and more than one race (7.8%); one (1.1%) participant declined to answer. The study was approved by the Institutional Review Board of Yale University. In this sample, 12 participants

(13.48%) scored above the clinical cutoff (≥14) on the depression subscale of the Depression Anxiety and Stress Scale [43], while 14 participants (15.73%) exceeded the clinical cutoff (≥10) on the anxiety subscale. Additionally, five participants (5.62%) self-reported an ADHD diagnosis.

2.1.2. Sample 2. Sample 2 consisted of 63 young adult females (ages 18–23 years, $M_{age} = 20.34$, $SD = 1.25$, 96.8% females) recruited in 2017 from Wellesley College (Massachusetts, USA). Details about the recruitment and sample have been described elsewhere [15]. Briefly, an initial online survey determined eligibility: 18 years or older, right-handed, no major medical illnesses, no probable substance abuse during the prior month, and no loss of consciousness >5 min. Participants were paid $10/h and were informed that they could earn an additional $25 during the AP. Participants predominantly identified as White/Caucasian (49.2%), followed by Asian (39.7%), Hispanic/Latin (9.5%), Black/African American (6.3%), and more than one race (3.2%); one (1.6%) participant identified as other or unknown racial/ethnic origins. Data on socioeconomic status (SES) were not collected. The study was approved by the Institutional Review Board at Wellesley College. In this sample, nine participants (14.29%) scored above the clinical cutoff (≥20) on the Center for Epidemiological Studies Depression Scale (CESD) [44] as set by Vilagut et al. [45]. Additionally, 11 participants (17.46%) exceeded the clinical cutoff (>40) on the state score of the Spielberger State–Trait Anxiety Inventory (STAI) [46]). Self-reported ADHD diagnosis was not collected in this sample.

2.2. Materials and Procedure

2.2.1. Brief Irritability Test (BITe). The BITe [47] is a 5-item self-report questionnaire, rated on a 6-point Likert type scale (1 = *never*, 2 = *rarely*, 3 = *sometimes*, 4 = *often*, 5 = *very often*, 6 = *always*), designed to assess irritability over the past 2 weeks. The total score is calculated by summing the score of each item. A high score on the BITe corresponds to a high level of irritability. In the current sample, the BITe demonstrated excellent internal consistency ($\alpha = 0.88$) and is thought to be the most reliable tool for measuring irritability in adults [48]. A recent psychometric review [49] identified the BITe as the most valid and specific tool for measuring irritability in young adults, effectively distinguishing it from related constructs such as depression, anger, hostility, and aggression with which it shows only small to moderate correlations [47]. BITe was used as a measure of trait irritability.

2.2.2. Affective Reactivity Index (ARI). The ARI is a 7-item questionnaire, rated on a 3-point Likert type scale (0 = *not true*, 1 = *somewhat true*, 2 = *certainly true*) designed to assess the severity, duration, and frequency of temper outbursts and irritable mood of the respondent and the impairment and burden associated with irritability. The total score is calculated by summing the first six items (excluding the impairment item). This scale has been designed for clinical populations of children and adolescents but has been used previously in young adults from the community [12, 15], although it does not capture the subtle variations in irritability present in community samples. In the current sample, the ARI demonstrated excellent internal consistency ($\alpha = 0.84$). ARI was also used as a measure of trait irritability, to allow for comparisons with pediatric studies that have predominantly used the ARI [22, 23].

2.2.3. The Affective Posner Task (AP). Both sets of participants completed the AP used in prior research [15]. Participants were asked to identify a target following a cue by button press (left or right). The target appeared in the same location as the cue (valid trials) for 75% of trials and in the opposite location (invalid trials) for 25% of trials. A sample trial of the task is depicted in Figure 2. Participants completed two blocks of the nonfrustration condition (100 trials) followed by two blocks of the frustration condition (100 trials). During the nonfrustration condition, participants were informed that they would win or lose 25¢ for every correct ("You Win!") or incorrect ("Wrong!") response, respectively, and they received accurate feedback on their task performance. During the frustration condition, participants were informed that accurate and *fast* responses were required to win 25¢. They were told that a "complicated formula" was used to determine the response speed requirement on a trial-by-trial basis; therefore, the best strategy was to respond as quickly and accurately as possible on each trial. Frustration was induced by providing participants rigged feedback on 60% of the correct responses ("Too slow!") and deducting money on those rigged trials. Participants received positive feedback ("You win!") in the remaining 40% of correct trials and won money, irrespective of their RT. At the end of each block, participants rated their feelings of frustration scale using a 9-point Likert scale from 1 = "not at all frustrated" to 9 = "extremely frustrated." This yielded two ratings from the nonfrustration blocks and two ratings from the frustration blocks; the average of each set of two ratings were used as a measure of state frustration during nonfrustration blocks and frustration blocks, respectively. This self-reported measure has been used extensively to index frustration [15, 23, 24, 50], and its test–retest reliability has been previously demonstrated [22]. A debriefing was done to assess participant deception following the task. Trial-by-trial RT and accuracy from each participant were used in the DDM analyses. Trials with RTs <200 ms were excluded from DDM analyses.

2.3. Statistical Analyses. We used hierarchical DDM (HDDM) [51] to estimate drift-diffusion parameters via the Bayesian modeling of participants' RT during the AP. HDDM is an open-source Python software package designed to construct hierarchical Bayesian DDMs, estimate posterior parameter distributions, calculate model fits (e.g., deviance information criterion [DIC] and posterior mean deviance), and plot model fit metrics (e.g., histograms and autocorrelation). Block type (frustration and nonfrustration) and trial type (valid and invalid trials) both served as two-level factors.

We tested different competing models in which the parameters were allowed to vary as a function of either block type (frustration and nonfrustration) and trial type (valid and invalid trials). The first model was the null model, where no parameters (neither drift rate, decision threshold, non-decision

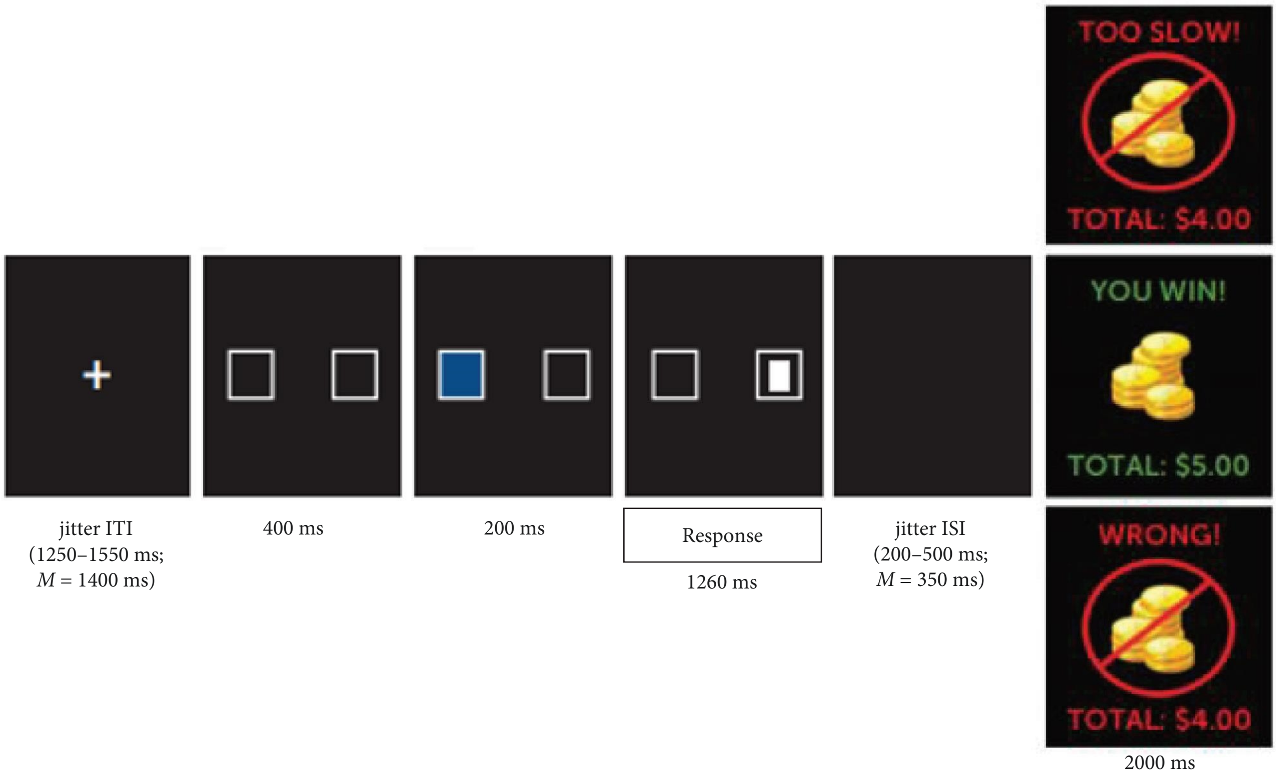

FIGURE 2: A sample trial in the affective Posner task.

time, or bias) were allowed to vary as a function of AP block or trial. The second model allowed the decision threshold parameter to vary as a function of block type (i.e., frustration/nonfrustration) and drift rate to vary by trial type (i.e., valid/invalid), providing five parameter estimates (i.e., decision threshold, frustration; decision threshold, nonfrustration; drift rate, valid; drift rate, invalid; and non-decision time). We hypothesized this model to be the best fitting model, as described in our introduction. The third model allowed the non-decision time parameter to vary as a function of frustration block type and drift rate to vary by trial type, again providing five parameter estimates (i.e., non-decision time, frustration; non-decision time, nonfrustration; drift rate, valid; drift rate, invalid; and decision threshold).

Drift rate was always split by trial type (valid versus invalid) given extensive research supporting processing efficiency differences between these two types of trials in inhibitory tasks [39–41]. Only the decision threshold and non-decision time parameters were split by block type (frustration vs. nonfrustration) to explore the two possible combinations of model fits (i.e., decision threshold by frustration/nonfrustration, drift rate by valid/invalid; non-decision time by frustration/nonfrustration, drift rate by valid/invalid). This decision was made as the relevant literature indicates that it is plausible that frustration may serve as an indirect speed–accuracy task manipulation [33], which would reduce the decision threshold parameter estimate and would also increase non-decision time [33, 42, 52].

Parameter estimates for each participant were then extracted from the best fitting group model. All models were run with 10,000 posterior samples with a burn-in of 2000 [51]. After determining the best fitting model, the Gelman–Rubin statistic [53] was calculated via HDDM, as a formal test of model convergence by comparing within- and between-chain variance of different runs of the same model. The Gelman–Rubin statistic was calculated from the comparison of chains of five models (10,000 iterations, 1000 burn-in each), with values <1.1 indicating good convergence [53]. As previously mentioned (see Participants section), two participants had a Gelman–Rubin statistic >1.1 and were removed from the final analytic sample [51, 53]. We determined model fit through the interpretation of the HDDM generated output of the respective models' DIC and deviance. Deviance can be taken as a Bayesian measure of fit or adequacy without consideration of model complexity. Since increasing complexity is accompanied by a better fit, models can be compared by the trade-off between these two quantities; DIC is a metric used to compare the relative fit of a set of Bayesian hierarchical models by combining a measure of goodness of fit and measure of model complexity. The model with the smallest DIC (or deviance) is estimated to be the model that would best predict a replicate dataset of the same structure [54].

2.4. Correlational Analyses and Regression Analyses. We examined the association between individual participant

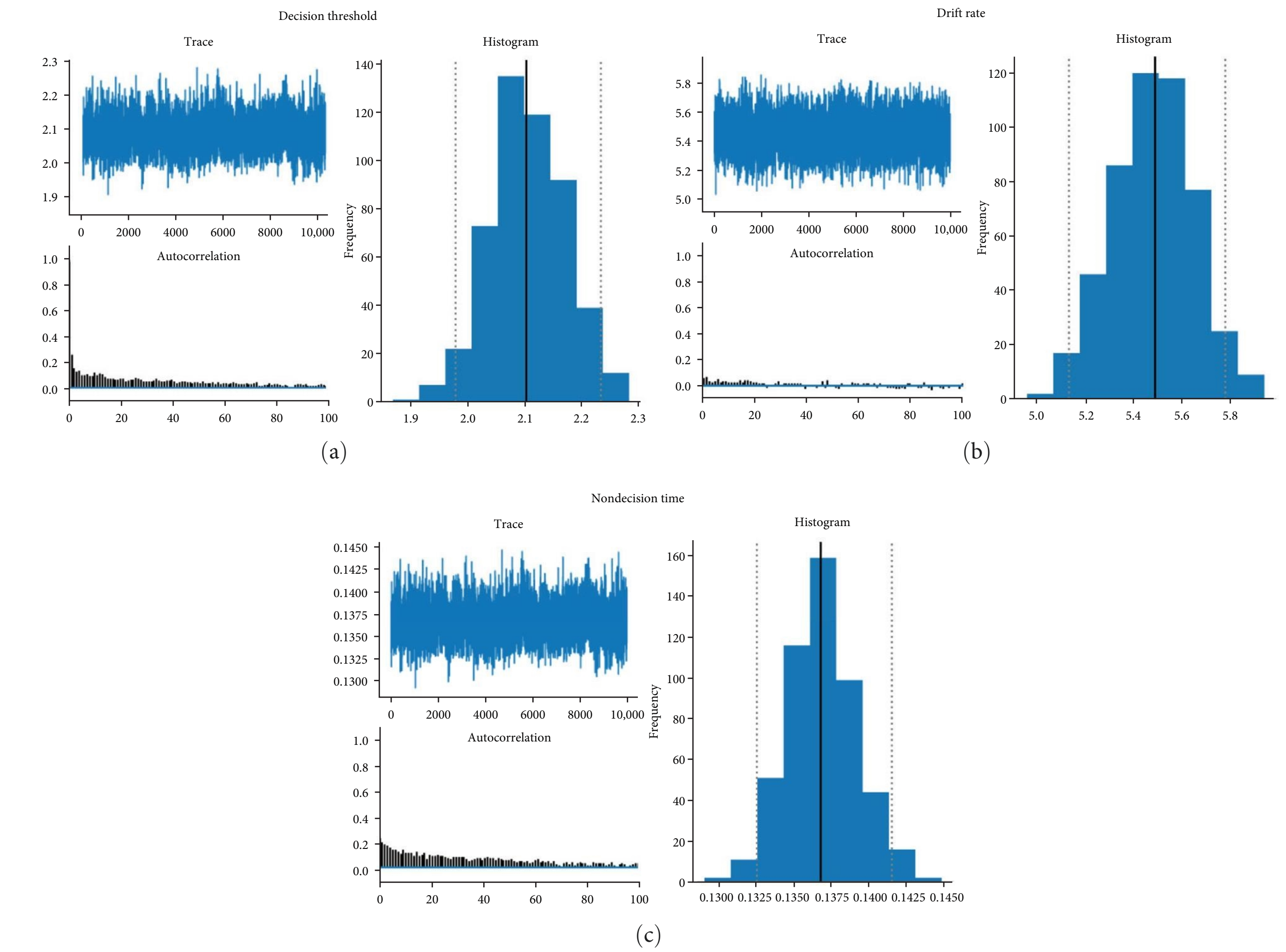

Figure 3: Posterior plots for the group mean of the threshold (a) (a), drift rate (v) (b), and non-decision time (t) (c) parameters of the null model. Posterior trace (a), autocorrelation (c), and marginal posterior histogram (b), where the solid black line denotes posterior mean and the dotted black line denotes 2.5 and 97.5 percentiles, are provided.

model parameter estimates and age, gender, state frustration (i.e., frustration ratings for nonfrustration and frustration blocks) and trait irritability (i.e., ARI and BITe scores), and mean RT and accuracy for nonfrustration and frustration blocks via Pearson correlations. We utilized the results of our correlational analyses to inform our decision on potential DDM parameter(s) and covariates to include as predictors in our regression analyses.

Multiple linear regressions were used to test if DDM parameters can predict state frustration and/or trait irritability (outcome variable), and whether these parameters continue to serve as a significant predictor when accounting for typical metrics used to assess AP performance (i.e., mean RT and accuracy during frustration condition). The sample location was dummy coded and used as a covariate in the analyses. Demographic covariates were included if significant associations emerged with the dependent variables used in our regression analyses.

HDDM was run in Python 3.8.3, and correlational and multiple linear regression analyses were conducted in RStudio.

3. Results

3.1. Model Fits. The inference algorithm used by HDDM, the Markov chain Monte Carlo (MCMC) simulation, requires the model chains to have properly converged. To informally assess model fit, we first performed visual sections of trace, autocorrelation, and marginal posterior plots for the parameters (Figure 3). Trace plots (top left graphs) for all three parameters did not exhibit abrupt changes or drifts, suggesting successful model convergence [51]. Second, autocorrelation levels (bottom left graphs) indicated good mixing; each parameter dropped to zero with lag (i.e., the number of past samples considered in the correlation). Third, the histograms showed all parameters to be approximately normally distributed.

The DIC is a commonly used criterion for assessing model fit in hierarchical models, where lower negative values indicate better fit [54]. The comparison of DIC and deviance values across all three models suggested that the model allowing the decision threshold to vary by block type

Table 1: Convergence statistics of the models examined.

Model	DIC	Deviance
Null model	−53,517	−53,858
Drift rate by trial type (valid vs. invalid) Threshold by block type (frustration vs. nonfrustration)	**−67,093**	**−67,745**
Drift rate by trial type (valid vs. invalid) NDT by block type (frustration vs. nonfrustration)	−63,860	−64,469

Note: Bold = best fitting model.
Abbreviations: DIC, deviance information criterion; NDT, non-decision time.

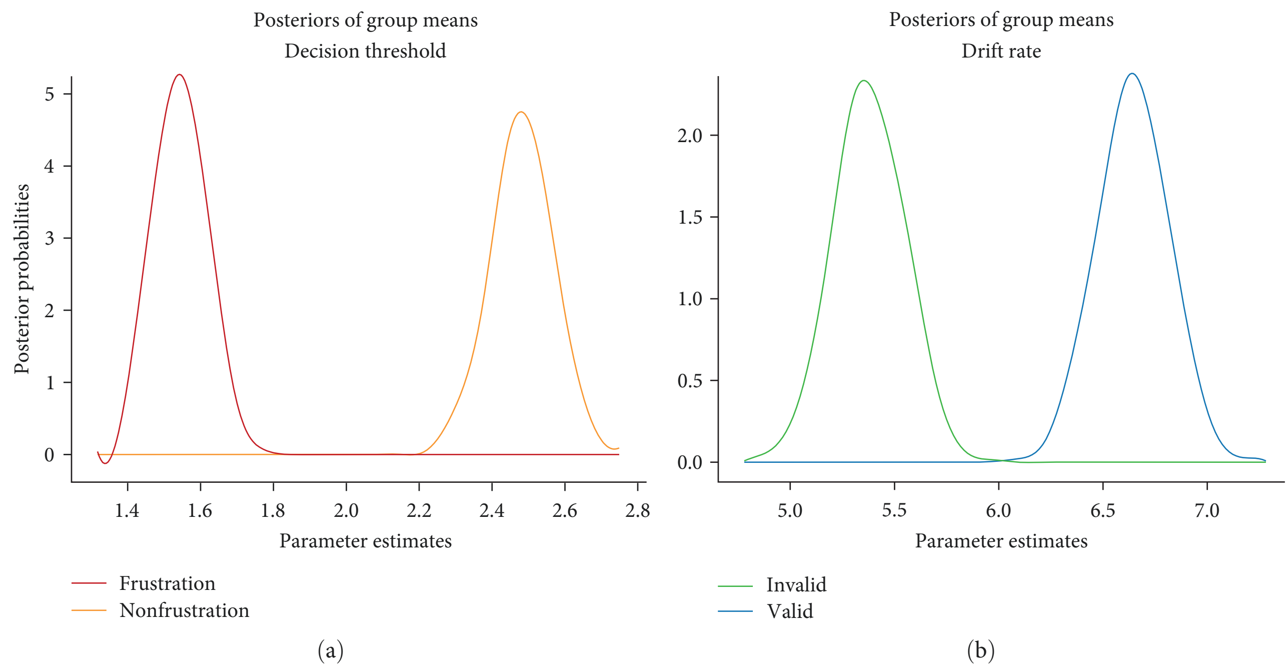

Figure 4: Posterior probability group means of decision threshold varying by frustration/nonfrustration blocks (a) and drift rate varying by valid/invalid trials (b) during the affective Posner task (AP).

(frustration versus nonfrustration) and drift rate to vary as a function of trial type (valid versus invalid) provided the best fit for the data (Table 1). Specifically, participants' processing efficiency decreased during invalid trials (relative to valid trials), a well-documented effect in the literature (e.g., [39]), and their performance shifted toward a preference for speed over accuracy in the frustration blocks (relative to nonfrustration blocks). Figure 4 shows the posterior probability group means of the decision threshold and drift rate parameters.

Thus, the two decision, threshold parameter estimates by blocks (i.e., frustration decision threshold and nonfrustration decision threshold) and the two drift rate parameter estimates by trial types (i.e., valid and invalid drift rate) were examined in subsequent analyses. To examine relative changes in decision threshold (between nonfrustration and frustration blocks) and drift rate (between valid and invalid trials), we calculated difference scores (i.e., Δ decision threshold calculated as nonfrustration decision threshold minus frustration decision threshold and Δ drift rate calculated as valid drift rate minus invalid drift rate, respectively).

3.2. Correlational Results. As shown in Table 2, state frustration (i.e., frustration ratings) in the frustration blocks was negatively correlated with the frustration decision threshold ($r = -0.25$, $p < 0.01$) and positively correlated with the Δ decision threshold (i.e., difference between the nonfrustration and frustration decision thresholds) ($r = 0.17$, $p < 0.05$). This suggests that the more frustration participants reported, the more likely they were to emphasize speed over accuracy in the frustration block, relative to the nonfrustration block.

State frustration in the frustration blocks was negatively correlated with mean RT during the frustration block ($r = -0.20$, $p < 0.05$), while state frustration in the *non*frustration block was negatively correlated with mean accuracy during the nonfrustration condition ($r = -0.19$, $p < 0.05$). Trait measures of irritability (i.e., ARI and BITe), as well as age and gender, did not correlate with any of the DDM parameters or traditional RT and accuracy metrics. Therefore, we did not purse any regressions with trait irritability measures as the outcome variables.

3.3. Regression Results. Two multiple linear regressions were conducted with self-reported state frustration in the frustration blocks as the outcome variable in order to examine the hypothesis that DDM parameter estimates of AP data improve predictive utility above and beyond typical metrics of performance. The first multiple linear regression included

Table 2: Pearson correlation matrix of measured variables.

Variables	M	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Decision threshold frustration	1.15	0.36	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
2. Decision threshold nonfrustration	2.04	0.69	0.14	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
3. Drift rate invalid	5.47	1.42	***0.29***	−0.15	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4. Drift rate valid	6.72	1.76	***0.39***	***−0.23***	***0.81***	—	—	—	—	—	—	—	—	—	—	—	—	—	—
5. Non-decision time	0.17	0.01	***-0.68***	0.07	−0.11	***−0.29***	—	—	—	—	—	—	—	—	—	—	—	—	—
6. Bias	0.37	0.06	***−0.41***	0.01	***0.45***	***−0.59***	***0.35***	—	—	—	—	—	—	—	—	—	—	—	—
7. Δ decision threshold	0.89	0.73	***−0.35***	***0.87***	***-0.29***	***−0.41***	***0.40***	***0.21***	—	—	—	—	—	—	—	—	—	—	—
8. Δ drift rate	1.25	1.04	***0.27***	**−0.18**	0.00	***0.59***	***−0.35***	***−0.38***	***−0.31***	—	—	—	—	—	—	—	—	—	—
9. Trait Irritability—ARI	1.78	2.13	−0.03	−0.12	0.07	0.03	−0.00	0.09	−0.10	−0.04	—	—	—	—	—	—	—	—	—
10. Trait Irritability—BITe[a]	11.51	4.40	0.08	−0.08	0.09	0.06	−0.06	−0.05	−0.11	0.02	***0.51***	—	—	—	—	—	—	—	—
11. State frustration—frustration ratings in frustration block	5.08	2.23	***−0.25***	0.05	0.10	−0.09	0.17	0.13	**0.17**	−0.02	***0.29***	**0.23**	—	—	—	—	—	—	—
12. State frustration—frustration rating in nonfrustration block	2.07	1.41	−0.06	−0.06	0.01	−0.06	0.13	0.01	−0.02	−0.12	***0.22***	***0.26***	***0.43***	—	—	—	—	—	—
13. Age in years	20.94	1.98	−0.07	−0.05	0.05	0.12	0.10	−0.00	−0.01	0.14	−0.03	0.02	−0.03	−0.09	—	—	—	—	—
14. Gender	—	—	−0.13	−0.01	0.01	0.02	−0.08	0.10	0.05	0.02	−0.06	**−0.20**	−0.07	**−0.21**	0.12	—	—	—	—
15. Nonfrustration RT (ms)	391.00	119.95	−0.15	***0.80***	***−0.59***	***−0.71***	***0.29***	***0.29***	***0.83***	***−0.38***	−0.10	−0.08	0.11	0.00	−0.13	−0.06	—	—	—
16. Nonfrustration accuracy (%)	98.93	1.61	**0.19**	**0.22**	0.09	0.12	−0.08	0.03	0.12	0.08	−0.09	0.10	0.05	**−0.19**	0.06	−0.00	0.05	—	—
17. Frustration RT (ms)	274.96	41.83	***0.68***	***0.20***	**−0.21**	**−0.19**	***−0.36***	−0.16	−0.14	−0.03	−0.05	−0.01	**−0.20**	0.01	−0.13	***−0.24***	***0.24***	−0.00	—
18. Frustration accuracy (%)	90.52	7.90	***0.42***	**0.40**	0.00	−0.08	−0.11	0.15	**0.17**	−0.13	−0.05	0.06	−0.16	−0.05	0.04	0.01	***0.28***	***0.44***	***0.34***

Note: Bold correlations = $p < 0.05$; bold and italic = $p < 0.01$; Δ decision threshold = decision threshold difference between the nonfrustration and frustration blocks; Δ drift rate = drift rate difference between the valid and invalid trials.

Abbreviations: ARI, affective reactivity index; BITe, brief irritability test; RT, response time.

[a]Four participants did not complete this questionnaire.

Table 3: Results of the multiple linear regression using frustration decision threshold, frustration RT, frustration accuracy, and sample location to predict state frustration during frustration.

State frustration	β	*SE*	*t*	*p*	95% CI	
					Lower	Upper
Intercept	9.68	2.46	3.93	0.000	4.81	14.56
Frustration decision threshold	**−1.45**	**0.56**	**−2.59**	**0.01**	**−2.56**	**−0.34**
Frustration RT	−0.01	0.01	−0.57	0.57	−0.01	0.01
Frustration ACC	−0.03	0.03	−0.94	0.35	−0.08	0.03
Sample location	−0.17	0.39	−0.43	0.67	−0.95	0.61
Model						
R^2	0.07					
Adj. R^2	0.04					
F (4, 127)	2.44, $p<0.05$					

Note: The bold values show the significant predictor. β = standardized beta.
Abbreviations: RT, response time; SE, standard error.

Table 4: Results of the multiple linear regression using Δ decision threshold, frustration RT, frustration accuracy, and sample location to predict state frustration during frustration.

State frustration	β	*SE*	*t*	*p*	95% CI	
					Lower	Upper
Intercept	10.84	2.27	4.77	0.000	6.34	15.33
Δ decision threshold	**0.54**	**0.27**	**2.02**	**0.04**	**0.01**	**1.08**
Frustration RT	−0.01	0.00	−1.15	0.25	−0.01	0.01
Frustration ACC	−0.05	0.02	−1.82	0.07	−0.09	0.01
Sample location	−0.25	0.39	−0.64	0.52	−1.02	0.52
Model						
R^2	0.09					
Adj. R^2	0.06					
F (4,127)	3.06, $p<0.05$					

Note: The bold values show the significant predictor. β = standardized beta; Δ decision threshold = decision threshold difference between the nonfrustration and frustration blocks.
Abbreviations: RT, response time; SE, standard error.

the decision threshold in the frustration block as a predictor, and the second multiple linear regression included the decision threshold difference between nonfrustration and frustration blocks (i.e., Δ decision threshold) as a predictor. Both models also included mean RT and accuracy during the frustration block (i.e., frustration RT and frustration accuracy) and controlled for sample location. For both regressions, the corrected variance inflation factors of all predictors were ≤1.97, which suggested acceptable levels of multicollinearity for regression analysis.

The first regression (Table 3) showed that only the decision threshold in the frustration block ($\beta = -1.45$, $p < 0.05$, 95% CI = [−2.56, −0.34]) was a significant predictor of state frustration. The mean frustration RT and accuracy and the sample location were not significant predictors of state frustration. This result indicates that lower decision threshold in the frustration block predicted self-reported state frustration in the frustration block, suggesting that the more participants were frustrated, the more likely they were to prefer speed over accuracy in the frustration block.

In the second regression (Table 4), only the decision threshold difference between the frustration and nonfrustration blocks ($\beta = 0.54$, $p < 0.05$, 95% CI = [0.01, 1.08]) was a significant predictor of state frustration. The mean frustration RT and accuracy and the sample location were not significant predictors of state frustration. Overall, a decrease in the decision threshold from nonfrustration to frustration blocks predicted self-reported state frustration in the frustration block, suggesting that when participants were frustrated, they were more likely to prefer speed over accuracy in the frustration block (relative to the nonfrustration block).

4. Discussion

The current study had two objectives. First, we applied a DDM to the AP in a sample of young adults to determine which model best fitted the data. Second, we evaluated whether individual differences in the latent cognitive factors identified by the DDM were uniquely associated with individual differences in trait irritability and state frustration.

This research has the potential to guide future research utilizing frustration-inducing tasks to better predict individual differences in irritability. First, we found that the best fitting model allowed drift rate (i.e., information processing efficiency) to vary by trial types of the AP (invalid versus valid trials), whereas the decision threshold (i.e., speed/accuracy trade off) parameter differed as a function of the frustration versus nonfrustration blocks of the AP, reflected by a shift toward an impulsive style of decision-making (preferring speed over accuracy) when frustrated. Second, we found that state frustration was predicted by a lower decision threshold during the frustration block and reduction in decision threshold between the nonfrustration and frustration blocks.

Consistent with our hypothesis, the model allowing the drift rate to vary as a function of trial type (valid versus invalid) and the decision threshold to vary by block type (frustration versus nonfrustration) provided the best fit for the data. The attenuated drift rate slope for invalid trials relative to valid trials suggests that the evidence accumulation process was slower and less efficient when participants were required to shift their attention during invalid trials. This is consistent with wider literature demonstrating that task difficulty is best captured by drift rate in tasks involving conflict or incongruent trials such as the Stroop, Eriksen, or Simon tasks [39–41].

Findings indicated that participants tended to reduce their decision threshold during frustration relative to nonfrustration blocks, requiring less evidence to accumulate before making a decision. Put differently, participants were more likely to respond during frustration blocks with a decision style characterized by prioritizing speed over accuracy, displaying a more impulsive (less cautious) response style. This change in response style during frustration (relative to nonfrustration) may be explained, at least partially, by a few factors. First, prior to the frustration blocks, participants were informed that they were now required to respond "correctly and quickly" in order to earn money, as compared to the first two blocks in which they were not informed about any speed requirement. This emphasis on speed, and the high occurrence of "too slow" rigged feedbacks, could have led participants to reduce their decision threshold in the frustration blocks [55, 56], even though they were explicitly instructed to respond as *quickly* and *accurately* as possible on all trials from the frustration blocks. Verbal prompts requiring participants to focus either on response accuracy or speed are the most commonly employed speed–accuracy manipulations [57, 58]. Generally, these manipulations elicit similar decision styles (i.e., changes in decision threshold parameter values) found in the current study [42].

Second, it is also plausible that increases in feelings of frustration evoked an impulsive (less cautious) style of responding (relative to nonfrustration blocks) characterized by faster but less accurate responses. Meta-analysis work [59] has showed that frustrative events (i.e., the omission of an expected reward) are associated with the activation of brain regions involved in acute threat response (i.e., thalamus, amygdala, and periaqueductal gray) and the deactivation of regions involved in the reward system (e.g., striatum) and top–down emotional regulation (e.g., ventromedial prefrontal cortex [vmPFC]). Therefore, it is possible that frustration-induced vmPFC deactivation patterns may impede its ability to effectively regulate negative emotional responses [60], via the inhibition of limbic regions. This, in turn, may impede the ability to withhold inappropriate responses and lead to faster responses and higher number of errors in the AP. Indeed, participants were significantly faster and less accurate in the frustration block as compared to the nonfrustration block (247.96 ms vs. 391.00 ms; 90.52% vs. 98.93% accuracy, respectively). Furthermore, according to the frustration–aggression hypothesis, frustration typically elicits anger [61], and since anger is associated with behavioral approach tendencies [62, 63], it is possible that the frustration manipulation in this task may have increased participants' motivation to respond as quickly as possible in order to earn the reward, which would thus translate to decreased response caution.

Although the decision threshold decreased between the nonfrustration and frustration conditions for all participants, the degree to which the threshold was reduced was related to participants' state frustration. Our regression results demonstrated that the degree of frustration reported by participants was significantly associated with a lower value of the decision threshold parameter in the frustration blocks and larger decrease in decision threshold between nonfrustration and frustration blocks. This suggests that the more frustration participants reported during the task, the more likely they were to shift toward an impulsive style of decision-making (preferring speed over accuracy) as the task conditions changed, reflected by decreases in decision threshold in the frustration block, relative to the nonfrustration block. Notably, these associations were significant even after controlling for traditional RT and accuracy metrics, supporting our hypothesis that DDM models of the AP would provide unique insight into the mechanisms underlying individual differences in state frustration.

The current findings demonstrate the promise of applying the DDM to understand the behavior of young adults with varying degrees of irritability on the AP. This study contributes to the emerging literature demonstrating the promise of computational models in examining associations between pediatric irritability and cognitive processes (i.e., attentional biases and cognitive flexibility). These studies found that irritability was associated with longer nondecision time (i.e., time spent on sensory encoding and motor response) to label emotional faces [64], and larger extra-decisional time bias (i.e., an index for preferential allocation of attention to angry faces) was associated with weaker amygdala connectivity in youths with high irritability [65]. Irritability was also associated with larger decrease in drift rate in the incongruent condition of the Eriksen flanker task with increasing levels of inattention [66]. However, the tasks used in those studies were not specifically designed to induce frustration. Given the relevance of frustrative nonreward to theories of irritability [1], applying the DDM to frustrative nonreward paradigms in pediatric samples may be a particularly promising domain in which to identify the latent cognitive processes associated with irritability. This, in turn, may reveal targets for mechanism-based interventions in children with clinically significant and impairing levels of irritability, such as those diagnosed with disruptive mood dysregulation disorder or oppositional defiant disorder.

Surprisingly, trait irritability was not related to any of the DDM parameters or traditional RT and accuracy metrics. A possible explanation for the null findings could be that cognitive tasks, such as the AP, are not sensitive enough to pick up individual differences in general trait [67]. Although the frustration manipulation of the AP increases self-reported frustration relative to the nonfrustration block, the frustration ratings in our sample ($M = 5.08 \pm 2.23$ on a 9-point Likert scale) indicate that participants experienced moderate levels of frustration. More powerful and ecological frustration manipulations may be necessary to detect individual differences in trait irritability within adult community samples. Moreover, it is also possible that these effects are present only in individuals with clinical levels of irritability. In our combined sample, 21 participants (13.82%) exhibited clinical levels of depression, and 25 participants (16.45%) had clinical levels of state anxiety. As high irritability is associated with higher levels of depression and anxiety in adults [68], it is possible that our sample may have included only a limited number of participants with clinical levels of irritability, potentially contributing to the null findings for trait irritability. However, recent research estimates that 1.8% of the general population may present clinical levels of irritability even in the absence of at least moderate depressive or anxious symptoms [68]. We did not assess the proportion of participants with clinical levels of irritability in our sample, as no clinical cutoff has been formally established for the BITe or ARI in adults. Future research on adult irritability could benefit from defining clinical cutoffs on these questionnaires. Furthermore, since ADHD was not an exclusion criterion for our research, it is possible that some participants in our sample may have an ADHD diagnosis or symptoms. This may have impacted the results, as Haller et al. [66] reported an interaction between irritability and inattention symptoms on processing efficiency in children. Thus, research involving clinical transdiagnostic samples is necessary to understand how the presence of comorbid symptom dimensions (e.g., depression, anxiety, and ADHD symptoms) impacts the associations between irritability, state frustration, and DDM parameters. Moreover, such research could help determine whether our findings are specific to state frustration or could be better explained by co-occurring internalizing or broader psychopathology symptoms. Notably, a previous study has shown that in children with and without chronic irritability, internalizing symptoms predicted frustration responses above and beyond irritability [69].

The null findings between trait irritability and DDM parameters may suggest unique associations between these DDM parameters and state frustration. We found low positive correlations between the state frustration and trait irritability measures in our sample. Frustration ratings during the frustration blocks were weakly to moderately correlated with ARI scores ($r = 0.29$, $p < 0.01$) and the BITe ($r = 0.23$, $p < 0.05$). While this is inconsistent with characterizations of individuals with elevated irritability experiencing having exaggerated responses to frustration relative to individuals with lower levels of irritability, and with recent evidence highlighting the central role of daily feelings of frustration in the symptomatology of youths with severe irritability [19], correlations between state frustration and trait irritability are mixed in the literature and may vary according to the informant and the nature of the sample. For example, in a community-based sample, child-reported frustration ratings during the AP and child-reported irritability were weakly to moderately positively correlated ($r = 0.26$, $p < 0.05$; [22]), which is consistent with our findings in young adults, suggesting that a small-to-medium correlation may be expected in nonclinical samples for self-reported measures of irritability. In another study, child-reported frustration ratings in the AP were not correlated with an average of parent and child reports of the child's irritability in a transdiagnostic clinical sample enriched for irritability ($r = 0.11$, $p = 0.13$; [23]). It is not clear whether this absence of correlation is due to the transdiagnostic clinical nature of the sample or the fact that parent and child reports were combined. In favor of the latter hypothesis, previous studies found only modest agreement between parent- and child-reported irritability probably due to different interpretations of items [70], which could have reduced power to detect a significant correlation. Therefore, it is still not clear whether a similar pattern of weak correlations between self-reported trait irritability and state frustration during the AP would be observed in samples with clinical levels of irritability. Using another frustration paradigm (i.e., frustration go/no-go task), Seymour et al. [71] showed that ARI scores predicted change in self-reported state frustration in a sample of children with normative to impairing irritability.

The discrepancy between state and trait may also reflect the potential neurobiological differences between trait irritability versus state frustration. Trait irritability is thought to primarily arise from low tonic striatal dopamine levels, whereas the emotional response characterizing frustration is thought to reflect blunted anticipatory phasic dopaminergic responding in the striatum to appetitive stimuli [72–75]. Taken together, future research applying DDM to frustrative nonreward paradigms should continue to include both state and trait measurements as probes for individual differences in irritability, as they may reflect different aspects of behavior.

There are limitations to consider when interpreting the current findings. First, our sample was mostly college students and nonclinical; therefore, the generalizability of our results is limited to this population. Second, due to the lack of a common measure of internalizing problems across both samples, we were unable to assess the effect of internalizing symptoms (depression and anxiety) on our findings. Third, our sample was 75.2% female. Although gender was not correlated to any of the DDM parameters, future work with more representative samples of both males and females is necessary. Fourth, SES data were not available in Sample 2, which prevented us for controlling for its effect. As the AP involves winning and losing real amounts of money, SES should be taken into consideration in future studies.

In summary, these results point to the utility of DDM parameters, specifically the decision threshold, for linking latent cognitive processes with individual differences in *state* frustration in a nonclinical young adult sample. Specifically, higher state frustration is associated with an impulsive decision-making style (preferring speed over accuracy) during frustration. These findings must be replicated in populations with clinical levels of irritability (and with measures of trait irritability) before any potential clinical implications can be drawn. If confirmed, the decision threshold may be considered as a possible intervention target for individuals with irritability. For example, future interventions could investigate whether increasing the decision threshold in frustrating contexts, through emotional regulation strategies or task-based training, may be beneficial for individuals with high levels of irritability.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure

An earlier version of this study has been presented as a poster at the American College of Neuropsychopharmacology (ACNP) 62nd Annual Meeting.

Conflicts of Interest

The authors declare no conflicts of interest.

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