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PAPER

Computational modeling reveals strategic and developmental differences in the behavioral impact of reward across adolescence

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Abstract

Studies of reward effects on behavior in adolescence typically rely on performance metrics that confound myriad cognitive and non-cognitive processes, making it challenging to determine which process is impacted by reward. The present longitudinal study applied the diffusion decision model to a reward task to isolate the influence of reward on response caution from influences of processing and motor speed. Participants completed three annual assessments from early to middle adolescence ($N = 387$, 55% female, $M_{age} = 12.1$ at Wave 1; $M_{age} = 13.1$ at Wave 2, $M_{age} = 14.1$ at Wave 3) and three annual assessments in late adolescence ($M_{ages} = 17.8, 18.9, 19.9$). At each assessment, participants completed a two-choice reaction time task under conditions of no-reward and a block in which points were awarded for speeded accuracy. Reward reduced response caution at all waves, as expected, but had a greater impact as teens moved from early to middle adolescence. Simulations to identify optimal response caution showed that teens were overly cautious in early adolescence but became too focused on speed over accuracy by middle adolescence. By late adolescence, participants adopted response styles that maximized reward. Further, response style was associated with both internalizing and externalizing symptoms in early-to-middle adolescence, providing evidence for the construct validity of a diffusion model approach in this developmental period.

KEYWORDS
adolescence, diffusion model, longitudinal, reward, speed-accuracy trade-off

1 | INTRODUCTION

Adolescence is a period of heightened risk for engaging in a range of risky and maladaptive behaviors (Chassin et al., 2016; Simons-Morton et al., 2011). This increased risk is thought to be driven in part by rapid changes in neural systems that underlie reward processing (Casey et al., 2008; Crone & Dahl, 2012; Schreuders et al., 2018; van Duijvenvoorde et al., 2016), leading to impulsive and maladaptive behavior in the context of rewards. Behaviorally, this is often evaluated by assessing the impact of reward or reward magnitude on task performance. To demonstrate developmental differences in the impact of reward, groups of adolescents are often compared to adults and/or children in cross-sectional studies (Galván et al., 2006; Jazbec et al., 2006; Padmanabhan et al., 2011), and longitudinal studies document within-person changes throughout adolescence or across adolescence and other developmental periods (e.g., Paulsen et al., 2015).

Despite documented developmental differences in ventral striatal activity in rewarding contexts (Braams et al., 2015; Geier et al., 2010;

van Leijenhorst et al., 2010), evidence for a differential impact of reward on behavioral task performance is less convincing. Although a few studies have found heightened reward effects among adolescents compared to adults (Cohen et al., 2010; Galván et al., 2006; Padmanabhan et al., 2011), many studies fail to observe such effects (Bjork et al., 2010; Geier et al., 2010; Hardin et al., 2007; Jazbec et al., 2006; Paulsen et al., 2015). These mixed findings likely reflect multiple methodological factors. Differences in age ranges studied, statistical power to detect interactions, reward manipulation, and task type certainly contribute to the inconsistencies in study results (see Kray et al., 2018). The present study aims to highlight and address two key issues in an effort to better align measurement with the construct of interest, improve measurement precision, and hopefully enhance consistency in results that will aid in clarifying the relation between behavior and its hypothesized neural substrates in the context of rewarding stimuli.

First, most studies rely on reaction time (RT) and accuracy as performance metrics. Reward effects on RT and accuracy are usually evaluated and interpreted separately, even though the interpretation of one parameter typically rests on the findings of the other. Consider a scenario in which a parent tries to reduce the amount of time spent doing homework by rewarding the child for completion speed. If the child finishes homework in less time, the contingency would be deemed a success. Now consider if accuracy declined along with completion time. Would declines in completion time accompanied by declines in accuracy be considered successful? What balance of speed and accuracy would lead a parent to conclude that reward improved behavior? In other words, the extent to which reward-induced speeding of responding is adaptive or maladaptive depends on changes in response speed, corresponding changes in accuracy, and how the changes in each serve to meet, or not meet, the goal of the specific contingency.

Interpretation of RT and accuracy is further complicated by the myriad processes that are involved in a response. Reaction time is often interpreted as one's degree of caution in responding or how much time is taken to consider response options (e.g., Steinberg et al., 2008; Teslovich et al., 2014); yet, RT represents the total time for stimulus encoding, information processing, response selection, and response execution. When reward (or any manipulation) impacts RT, no inferences can be made regarding which part(s) of the response process is driving those effects. Fosco and colleagues (2017) illustrated this point by showing that multiple components of a response are impacted by stimulant medication, but not all in the same direction or to the same degree. While it is possible that changes in RT among adolescents represent changes towards a more impulsive response style, this needs to be empirically evaluated with methods that parse multiple processes that impact responding and directly speak to speed–accuracy tradeoffs.

Second, unless a metric is clear in what constitutes best performance (e.g. 100% accuracy), making inferences about poor or maladaptive performance often requires a reference group that is thought to exhibit normative behavior. When attempting to answer developmental questions, adolescents are often compared to adults as the reference group (e.g., Galván et al., 2006; Geier et al., 2010; Geier & Luna, 2012; Hardin et al., 2007; Padmanabhan et al., 2011).

Research Highlights

- Reward differentially impacts response caution from early to middle adolescence
- Responding is overly cautious in early adolescence but not cautious enough by middle adolescence
- Late adolescents adopt optimal response strategies that maximize reward
- Response caution relates to both internalizing and externalizing symptoms

Within adolescence, teens with a substance use disorder might be compared to adolescents without a substance use disorder (Chung et al., 2011). Any difference between the groups is typically interpreted as aberrant or maladaptive responding relative to the reference group. Such logic may be problematic. For example, there is evidence that adults may adopt response strategies that are overly cautious during speeded tasks (Evans et al., 2019), which may exaggerate apparent adolescent-related impulsive responding when adults are the reference group.

1.1 | Computational modeling

Computational modeling overcomes these two challenges by disentangling multiple components of responding. Evidence accumulation models are one widely-used class of decision-making models (Brown & Heathcote, 2008; Ratcliff, 1978) that can be used to extract separate measures of response caution, bias, stimulus processing speed, and encoding/motor time to provide more specific metrics for evaluating performance in RT tasks. These models assume that the decision process involves sequentially sampling and accumulating information from the stimulus until the amount of accumulated information reaches some threshold, indicating that a choice has been selected. For binary choice models, such as the diffusion decision model (DDM), each sample of information pushes the evidence towards one of two boundaries, which represent the two choices. Once the evidence reaches a boundary, it indicates that a choice has been selected, and the motor response is initiated.

The DDM integrates RT and accuracy data to decompose responses into several parameters representing psychologically-distinct processes (Ratcliff, 1978; Ratcliff, 2006; Ratcliff & Rouder, 1998; Voss et al., 2013; see Figure 1). Drift rate reflects the speed or efficiency of information accumulation. Non-decision time encompasses time spent outside of the decision-making process, including stimulus encoding and motor response execution.

Boundary separation is the critical parameter of interest in the present study. Many behavioral studies in adolescence aim to evaluate how various manipulations (e.g., rewards, the presence of peers, social feedback, etc.) impact teens' response style. Do teens respond

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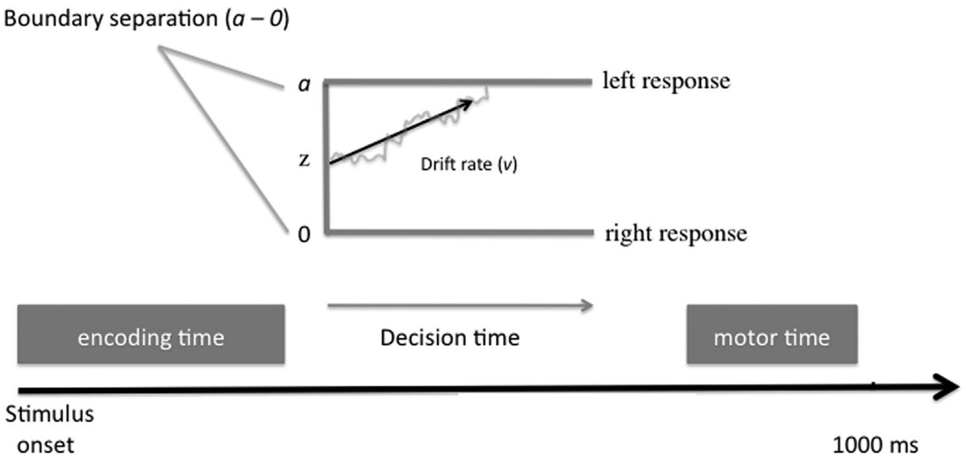

FIGURE 1 Schematic of the drift diffusion model (reprinted with permission from Moustafa et al., 2015). Boundary separation (*a*) reflects an individual's degree of caution in responding; wider/higher boundaries indicate a more cautious response style, whereby greater amounts of information are needed to make a decision. Drift rate (*v*) represents the rate of information accumulation. Non-decision time (*Ter*) encompasses time unrelated to decision making, including time for stimulus encoding and response execution

too quickly without considering their choices when peers are present? Does the threat of punishment lead teens to respond more cautiously? Estimates of boundary separation can best answer these questions because it captures how cautiously a participant responds and, thus, provides greater precision in construct measurement than simply using RT.

When the evidence accumulation process begins, boundaries can be set either close to the starting point of the decision process or farther apart. When boundaries are narrow and close together, relatively little information is needed for a decision to be made, resulting in faster but less accurate responding. As boundaries widen, responding becomes more accurate because more information is accumulated before the threshold is reached, though this increased accuracy occurs at the cost of slower responses. Individuals differ in their typical degree of boundary separation, and boundaries can be raised or lowered based on experimental manipulations. For example, providing participants with instructions that emphasize accuracy over speed increases boundary separation (Voss et al., 2004). Rewarding speed of responding lowers boundary separation (Fosco et al., 2017; Glickman & Usher, 2019), and punishing inaccurate responses increases boundary separation, as expected (Fontanesi et al., 2019).

In addition to isolating metrics that reflect caution (or lack thereof) in responding, the DDM also permits calculation of optimal boundary separation. Rather than recruiting a reference group, such as adults or children, and assuming that the non-adolescent group is engaging in ideal response patterns, the DDM can identify the optimal degree of caution for each participant that serves to maximize an individual's performance on a task (such as maximizing points earned during a reward task), given that individual's drift rate (stimulus processing) and the contingencies of the task (Simen et al., 2009). Thus, the ideal degree of caution is calculated as the level of boundary separation that maximizes the reward-rate, given the task parameters. With this approach, optimal boundary separation can serve as the reference point to which performance is compared. We can then evaluate how much participants' actual boundary separation deviates from their optimal boundary separation and whether this deviation changes developmentally. If actual boundary separation is higher than optimal, it suggests that the participant was overly cautious. If actual boundary separation is lower than optimal, it suggests the participant did not exert appropriate levels of caution, reflecting the kind of rash response style that is often of interest in studies of adolescent development.

1.2 | Current study

The present study quantifies how response caution is influenced by reward in adolescence. It improves upon previous studies by (1) isolating response style/response caution using computational modeling, (2) evaluating teens' actual degree of response caution relative to their optimal degree of caution, and (3) using a longitudinal design that allows for examining change over the course of adolescence. Consistent with previous diffusion model work (e.g., Fontanesi et al., 2019; Fosco et al., 2017), we predicted that introducing reward for speeded accuracy would reduce caution (boundary separation) across all six assessment waves, but that the effect of reward on boundary separation would be greatest in middle adolescence (Wave 3 in the current study). Although we are not aware of previous work that has empirically derived the reference point to which performance is compared, developmental neuroscience models posit that impulsive responding should peak around age 15 (Casey, 2015) and then decline. We therefore hypothesized that boundary separation will become lower (i.e., less cautious) than optimal from early to middle adolescence and will increase in late adolescence. Finally, because the deviation from optimal boundary separation is a new index in this area of research, we evaluated its construct validity by assessing how the intercept and slope of deviation relates to temperament and psychopathology—two domains of variables that are theoretically relevant to a cautious or rash response style.

TABLE 1 Participant characteristics at wave 1

Age	12.1 (0.59)
Sex (% Female)	55%
IQ	107.4 (11.2)
Ethnicity	
% Caucasian	83%
% African American	9%
% Hispanic/Latino	2%
% Asian/Pacific islander	1%
% Other/ multi-racial	5%

Note: Unless otherwise stated, values represent the mean (SD). IQ was estimated from the Reynolds Intellectual Screening Test (RIST).

2 | METHODS

2.1 | Participants

Participants included 387 families (caregiver and adolescent) who were recruited for a longitudinal study of adolescent substance use. The community sample was recruited via random digit dialing, resulting in a sample representative of the area in which the study was conducted (Erie County, NY, USA; see Table 1 for participant characteristics)[1]. Participants were eligible for the study if they were 11—12 years old at recruitment/Wave 1, had no disabilities that would interfere with their ability to complete the assessments, and had a caregiver willing and able to participate.

2.2 | Procedures

Parental consent and child assent were obtained at each visit. Participants completed annual laboratory visits for Waves 1—3 (*M (SD)* child ages = 12.1 (0.58), 13.1 (0.59), and 14.1 (0.59) across waves) and Waves 7–9 (*M (SD)* ages = 17.8 (0.70), 18.9 (0.77), and 19.9 (0.72)) of the study. Data collection in Waves 4–6 was conducted via an automated phone survey and assessed only substance use variables, which are not the focus of this study. Laboratory visits included questionnaires assessing the teens' social, emotional, relational, and psychological functioning, as well as several computerized tasks. The Point Scoring Reaction Time task (Colder et al., 2011) was designed to assess sensitivity to reward and punishment and was administered at every in-person visit. Retention ranged from 94% at Wave 2 to 80% at Wave 9.

2.3 | Measures

Questionnaire data are publicly available through ICPSR (https://www.icpsr.umich.edu/web/ICPSR/studies/37620), and the E-prime task file is available on the developers' website (http://www.acsu.buffalo.edu/~program2/ubafdp/R_tasks.html). Task data are not publicly available due to limited resources stemming from financial constraints from the study's conclusion.

2.4 | Point scoring reaction time task for children–revised (PSRTT-CR)

The PSRTT-CR (PSRT for short) required participants to discriminate between odd and even numbers[2]. Stimuli consisted of a double-digit number presented below a colored circle (see Figure 2). Below the task stimuli, the number of points gained or lost on each trial, as well as a running total, was presented at the end of each trial. Participants pressed the left and right buttons on a response box to indicate whether the stimulus was an odd or even number. After a 20-trial practice block (70% accuracy required to advance to practice blocks), teens completed four, 50-trial experimental blocks in which contingencies were manipulated. Throughout all blocks, participants lost 2 points for incorrect responses. This response cost was the only contingency in the *no-reward* block. The *reward* block introduced the possibility of gaining points, and the amount of points earned was based on speed of RT for correct responses (points = 835/RT [in ms]). Children were told that they could redeem their points for a prize; three tiers of prizes were available depending on how many points they earned. The *punishment* and *post-punishment* blocks followed, but are not relevant for the current study (see Colder et al., 2011 for details). After each 3-s trial, a 500-ms feedback screen presented an "X" or "O" for incorrect and correct responses; respectively, along with the number of points earned/lost on that trial and a running point total.

2.5 | Psychopathology

Wave 1 and Wave 7 measures were used in this study (see Data Analytic Plan). All measures described below required the parent to indicate how well a given statement described their child (or themselves in the later waves) via a likert scale. The disruptive behavior disorder rating scale (DBD-RS; Pelham et al., 1992) and Child Behavior Checklist (CBCL; Achenbach & Rescorla, 2001) were used for construct validation purposes. The DBD-RS assesses DSM symptoms of ADHD inattention ($\alpha = 0.91$), ADHD hyperactivity/impulsivity ($\alpha = 0.83$), oppositional defiant disorder ($\alpha = 0.88$), and conduct disorder ($\alpha = 0.71$). The CBCL is a broadband measure of children's social, emotional, and behavioral functioning. The current study utilized T-scores from the overall externalizing ($\alpha = 0.90$) and internalizing scales ($\alpha = 0.88$).

In later waves (7–9), participants self-reported their symptoms and functioning using the Adult Self-Report, a developmentally-appropriate extension of the CBCL (Achenbach & Rescorla, 2003) with the same response scale described above. The DBD-RS was not

[1] At the time of recruitment, 98.5% of households in the county had a landline phone.

[2] Reaction time data from this task for Waves 1-3 are reported in Colder et al., 2013.

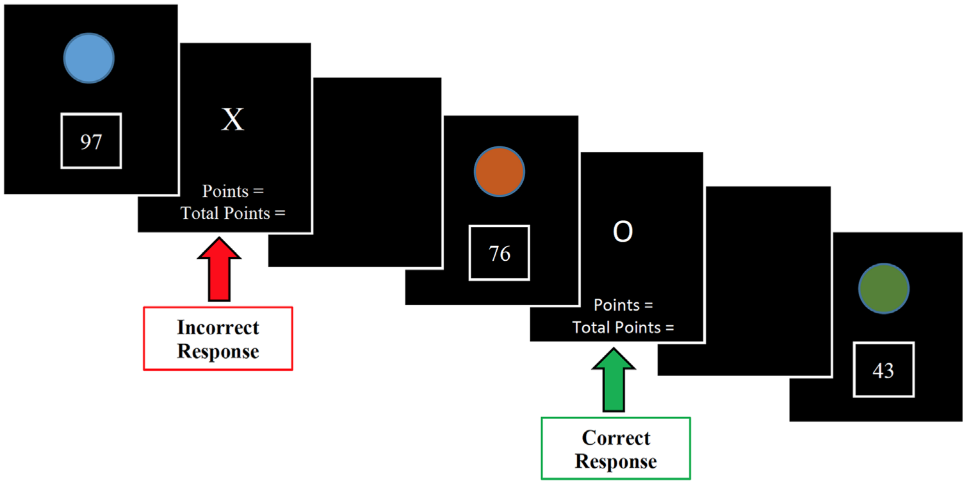

FIGURE 2 Trial structure of the Point Scoring Reaction Time Task for Children –Revised. Children were required to use a response box to indicate if the number presented was odd or even

collected at later waves, so the overall internalizing (α = 0.93) and externalizing (α = 0.90) T-scores from the ASR were the only indicators of psychopathology used for Waves 7–9.

2.6 | Temperament

Parent report of temperament was assessed with the Sensitivity to Punishment and Sensitivity to Reward Questionnaire for Children–Revised (SPSRQ-CR; Colder et al., 2011), as well as the Early Adolescent Temperament Questionnaire–Revised (EATQ-R; Ellis & Rothbart, 2001). We selected the scales most theoretically relevant for boundary separation. These included the anxiety (α = 0.60), drive (α = 0.73), response to social approval (α = 0.62), and impulsivity/fun seeking (α = 0.75) scales from the SPSR-Q and the effortful control (α = 0.89) and surgency (α = 0.62) scales from the EATQ-R.

At Waves 7–9, temperament was assessed using the sensitivity to punishment (α = 0.84) and sensitivity to reward (α = 0.75) scales from the adult version of the SPSRQ (Torrubia et al., 2001) and the effortful control scale of the Adult Temperament Questionnaire (α = 0.80; Evans & Rothbart, 2007).

2.7 | Data analytic plan

2.7.1 | Drift diffusion parameter estimation

As we were primarily interested in the three main diffusion model parameters (boundary separation, drift rate, non-decision time), we used the "EZ diffusion model" (EZDM) method (Wagenmakers et al., 2007). Previous work shows that EZDM provides inferences about these main DDM parameters that are highly similar to those drawn from more complex estimation methods (Dutilh et al., 2019; van Ravenzwaaij et al., 2017) and may have superior recovery of individual differences in parameter values when compared to other DDM fitting procedures (van Ravenzwaaij & Oberauer, 2009).

Prior to EZDM parameter estimation, individual trials were separated by wave and by experimental condition for each participant. Following previous DDM studies in children (Ratcliff et al., 2012), RTs < 300 ms were removed as "fast guesses" (1.2% of all trials). Upper RT exclusion boundaries were then computed separately for each participant and wave (the median RT plus three times the interquartile range) and RTs greater than these boundaries were removed as slow outliers (1.6% of all trials). Finally, the EZDM R code provided by Wagenmakers et al. (2007) was used to estimate parameters. In EZDM, the two boundaries represent correct and incorrect responses. Following the recommendation from the original study, accuracy scores for individuals with no errors (1.00) were transformed using the following "edge correction" formula: accuracy = 1-1/2*n*, where *n* is the number of trials in the block.

Accurate estimation of diffusion model parameters can be challenging when the number of trials in each condition is relatively low and when errors are rare, both of which are true of the PSRT data (see Table S2). We therefore conducted a simulation/recovery study to assess the accuracy of our parameter estimation procedures for recovery parameters from data with similar features to the PSRT. As described in detail in Supplemental Materials 2, these analyses suggested that the EZDM procedures were highly effective at recovering the parameters of interest (*v*, *a*, and *Ter*) from data with similar trial numbers and error rates to the empirical PSRT data.

2.7.2 | Calculation of optimal boundary separation

We followed the general procedure of Simen and colleagues (2009) to identify the optimal levels of boundary separation for each participant at each wave. The goal was to identify the level of caution that would produce the highest point total in the reward block. Optimal boundary separation was only computed for the reward block because, technically, the optimal response in the no-reward block is no response (i.e., when inaccuracy is penalized, then providing no response is the most adaptive thing to do).

The optimal degree of boundary separation is not a static characteristic. It varies for each individual and across time because what is optimal is influenced by one's level of discriminability (drift rate) and duration of encoding/motor time (non-decision time); thus, optimal boundary separation was computed at each time point, given each participants' drift rate and non-decision time. To that end, we simulated 20,000 trials from the diffusion model with the estimated parameter values of drift rate and non-decision time for each participant, combined with a specific value of boundary separation. We then calculated the total points earned (per the reward structure of the task) for that level of boundary separation. This simulation structure was used to conduct a parameter search for the boundary separation value that produced the highest number of total points using the optimize function in R.

The results provide an optimal value of boundary separation for each participant. These optimal values were used to compute the extent to which each participant was more or less cautious than optimal (Deviation from optimal boundary separation = actual boundary separation–optimal boundary separation). Positive values indicate overly cautious responding, and negative values indicate less-than-optimal caution. Given the novelty of calculating optimal boundary separation in the current context, we performed two validity checks. First, we compared the actual number of points earned during the reward block with the points that would have been earned if participants engaged in their optimal strategy. Points earned under optimal conditions should be higher than actual points earned. Second, we regressed the absolute value of individual's deviation from optimal boundary separation on their actual earned points. Greater deviation should be associated with earning fewer points on the task.

2.8 | Latent growth curve modeling

Latent growth curve modeling utilizes observed data across multiple time points to estimate a latent intercept (starting point) and slope (rate of change) factor. Latent growth curves were estimated in MPlus version 8 (Muthén & Muthén, 2017). Across models, growth was modeled as a function of assessment Wave, and robust maximum likelihood estimation was used to account for non-normality. A series of latent growth curves were estimated to evaluate, (1) the impact of reward on boundary separation across time, and (2) how deviation from optimal boundary separation changes throughout adolescence. A benefit of latent growth curve modeling is the estimation of a random intercept and slope. The random intercept reflects variability around the mean starting point, and the random slope reflects variability around the mean growth trajectory. Therefore, our models account for individual differences in both initial values and rates of change over time. For all models, we took a systematic model-building approach to evaluate whether a linear, quadratic, or piecewise growth model provided the best fit to the data. For sake of space, only the final model is presented in main text, but the full model-building procedure is described in supplemental materials. Although we tested age as a covariate, it was unrelated to the intercept and slope terms and was therefore not retained.

First, in order to evaluate the impact of reward on boundary separation, growth curves were estimated for the no-reward and reward blocks. A piecewise growth model with two-intercepts and slopes was specified to model growth in boundary separation in reward and no-reward conditions. The first component of the piecewise model occurred from Waves 1–3 and the second from Waves 7–9. Piecewise models separate the pattern of change into multiple linear "pieces." Each piece of the model can have its own intercept and slope parameters and is particularly useful for modeling non-linear growth when there are inflection points in the pattern of change. For the present study, this model was selected for several reasons: (1) a piecewise model with two intercepts and slopes fit the data well and provided superior fit, relative to a linear model, (2) it accounted for the time gap between assessments 3 and 7, and (3) Waves 1–3 and Waves 7–9 capture early to middle adolescence and late adolescence, respectively. Brain maturation in regions implicated in reward are thought to develop at different rates during these developmental periods.

Second, a parallel growth model with the best-fitting reward and no-reward growth curves was specified. A parallel growth curve model allows one to model growth (intercept and slope factors) in two or more constructs simultaneously and permits examination of how growth in two variables may covary (Curran et al., 2010). Put another way, it examines how constructs might develop in parallel. In this case, we simultaneously modeled boundary separation in the reward and no-reward conditions to evaluate reward effects on boundary separation. Nested model tests were conducted to determine whether the starting point of growth (intercepts at assessment Waves 1 and 7) and rate of change (slopes in each linear piece) in boundary separation was the same in the reward and no-reward conditions. A significant decrement in fit when the growth parameters were constrained to be equal for the no-reward and reward conditions would indicate a difference across conditions (a reward effect). Third, specification of the growth curve of deviation from optimal boundary separation followed the same model-building steps as outlined above for the reward and no-reward blocks.

Finally, to provide evidence of construct validity of the deviation from optimal variable, we evaluated a set of psychopathology and temperament predictors that have theoretical and empirical relations to cautious versus rash responding. Indicators of psychopathology and temperament at Wave 1 and Wave 7 were regressed on the intercept and slope of the growth model from step three above. This addresses the question of whether psychopathology and temperament are associated with growth in boundary separation. Given the number of individual predictors, we first conducted nested tests to evaluate whether including the set of predictors within a domain (e.g., the set of psychopathology variables and then the set of temperament variables) improved model fit, relative to a model in which all predictors were constrained to zero. This process provides an omnibus test of whether the total set of predictors improves model fit, relative to a model without the predictors. If the nested test suggested significant improvement in model fit, we then interpreted individual effects. Psychopathology and temperament were analyzed in separate models because the goal was not to answer questions regarding which variables accounted for unique variance in the outcome, but rather to demonstrate that

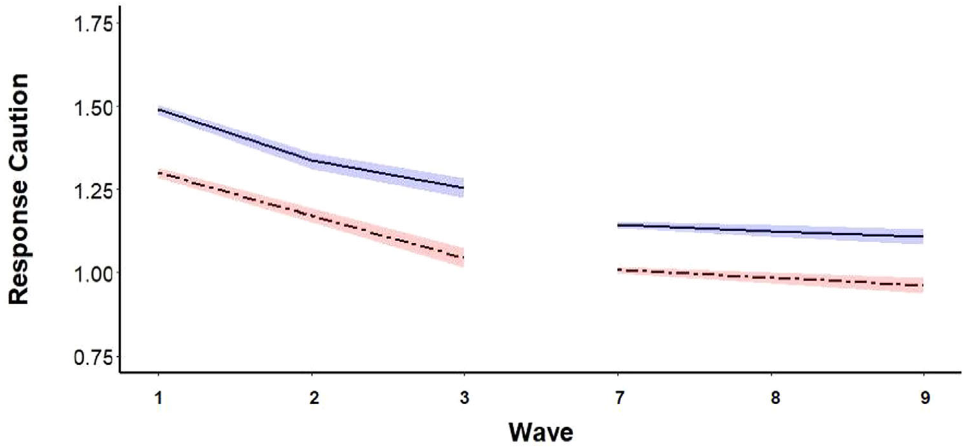

FIGURE 3 Model-implied values of response caution across assessment waves. Higher values of boundary separation reflect more cautious responding. Participants were approximately 12 years old at Wave 1, and Waves are approximately 1-year intervals. Solid lines with blue confidence intervals are the no-reward condition, and dashed lines with red confidence intervals are the reward condition

the deviation variable relates to clinically- and theoretically-relevant constructs.

3 | RESULTS

3.1 | Longitudinal changes in response caution

The two-intercept piecewise growth model with a freely estimated Wave 2 slope loading for no-reward provided a strong fit to the data ($\chi^2(6) = 11.02$, $p = 0.09$; CFI = 0.99, RMSEA = 0.05; SRMR = 0.04; see Figure 3). Boundary separation was relatively high at the first intercept/age 11 (intercept M = 1.49) and decreased across Waves 1–3 (slope $M = -0.24$, $p < 0.001$; slope loadings = 0, 0.65, 1 across Waves 1–3, respectively). Significant variance was present in both the first intercept ($\sigma^2 = 0.05$, $p < 0.001$) and slope ($\sigma^2 = 0.04$, $p = 0.02$). In later waves, the intercept was 1.15, and values of boundary separation continued to decrease, albeit at a slower rate than at Waves 1–3 (slope $M = -0.02$, $p = 0.001$; slope loadings = 0, 1, 2 across Waves 7–9). Significant variance in the intercept was still observed ($\sigma^2 = 0.03$, $p < 0.001$), but there was no evidence of variability in the slope of change in late adolescence ($\sigma^2 = 0.001$, $p = 0.60$), suggesting that all participants demonstrated similar reductions in boundary separation across these Waves 7–9.

For the reward condition, the two-intercept piecewise model with two linear slopes also provided an excellent fit to the data ($\chi^2(7) = 10.05$, $p = 0.19$; CFI = 0.99, RMSEA = 0.03; SRMR = 0.04; see Figure 3). Average boundary separation at the first intercept was 1.30 and decreased from Wave 1 to 3 (slope $M = -0.13$, $p < 0.001$). In the second piece of the model, the intercept was 1.01 and again showed a significant decrease from Wave 7 to 9, though at a slower rate than observed at Waves 1–3 (slope $M = -0.02$, $p < 0.001$). Similar to the results in the no-reward condition, significant variance was present in both intercepts ($\sigma^2 = 0.05$, $p < 0.001$ and $\sigma^2 = 0.03$, $p < 0.001$ for the first and second intercept, respectively). In contrast, teens did not demonstrate significant variability in rates of change from Waves 1–3 ($\sigma^2 = 0.004$, $p = 0.17$), but significant variability was present in rates of change from Waves 7 to 9 ($\sigma^2 = 0.003$, $p = 0.03$).

To summarize, participants' boundary separation decreased from early to middle adolescence and again through late adolescence. Teens showed significant individual variability in their starting values of boundary separation in both early and late adolescence, regardless of reward context. In the no-reward block, there was significant individual variability in rate of change in boundary separation from early to middle adolescence, but rates of change did not vary in late adolescence. In the reward block, the opposite pattern of individual variability was observed. There was no evidence for individual variability in change from early to middle adolescence but there were significant individual differences in change across late adolescence. While these results are an important first step in documenting developmental changes in impulsive versus cautious response styles, the important theoretical test is whether developmental changes differ as a function of reward context.

3.2 | Reward effects on response caution across waves

Next, we simultaneously modeled growth in boundary separation in the reward and non-reward conditions. Reward significantly reduced boundary separation at both intercepts, as evidenced by a decrement in model fit when intercepts were constrained to be equal (akin to a main effect in an moderation model; intercept for Waves 1–3: $\Delta\chi^2$ (1) = 152.90, $p < 0.001$; intercept for Waves 7–9: $\Delta\chi^2$ (1) = 323.62, $p < 0.001$). In addition to a main effect, reward impacted the slope of boundary separation change from Waves 1 to 3, such that boundary separation showed a more rapid decline in the reward condition ($\Delta\chi^2$ (1) = 35.64, $p < 0.001$). In contrast, reward did not impact the slope of change across Wave 7–9, as constraining the reward and no-reward slope to be equal did not impact model fit ($\Delta\chi^2$ (1) = 0.40, $p = 0.53$; see Figure S1a for the path diagram of this final model). Because there is

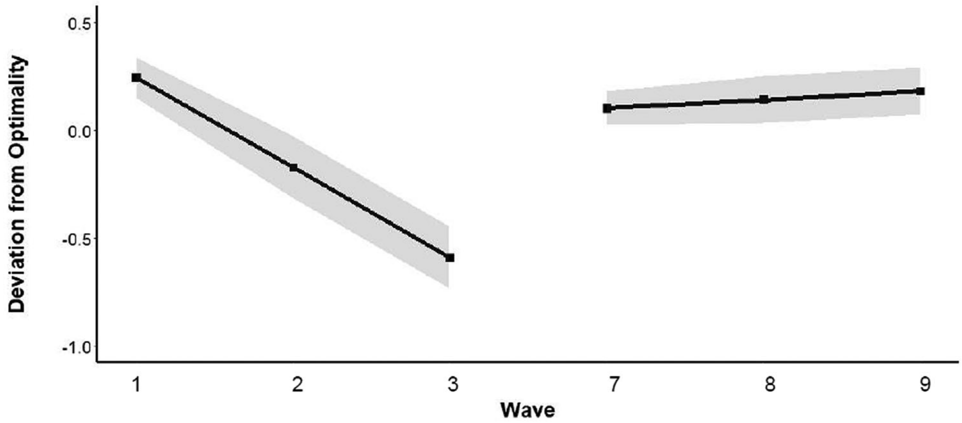

FIGURE 4 Values represent the difference between one's actual boundary separation and the optimal boundary separation to maximize points on the task. Values above zero reflect overly cautious responding. Values below zero reflect responding that maladaptively emphasizes speed over accuracy

no simple way to compute effect sizes at each time point in the latent growth curve framework, we computed Cohen's *d* between the no-reward and reward conditions cross-sectionally at each Wave. Cohen's *d* were 0.57, 0.66, and 0.80 across Waves 1–3, respectively, and 0.64, 0.67, and 0.73 across Waves 7–9, suggesting moderate to large effects of reward.

These analyses demonstrate a significant main effect of reward across time. They further demonstrate that reward had a greater impact as teens moved from early to middle adolescence. However, reward impacted performance similarly across late adolescence.

3.3 | Deviation from optimal response caution

Validity checks showed that, as expected, the total points participants would have hypothetically earned if they utilized optimal levels of response caution was significantly higher than that total points they actually earned at each assessment wave (*ts* = 4.03 – 7.40; all *ps* < 0.001). Furthermore, greater deviation from optimal boundary separation was associated with fewer earned points across all waves (βs = -0.20 – -0.36, all *ps* < 0.001), demonstrating that suboptimal boundary separation did indeed result in worse reward outcomes.

Similar to the approach taken with the no-reward and reward growth curves, a two-intercept piecewise model fit the data well ($\chi^2(6) = 6.16$, $p = 0.41$; CFI = 0.99, RMSEA = 0.01; SRMR = 0.02). As shown in Figure 4, teens were significantly more cautious than optimal at Wave 1 (intercept $M = 0.04$, $p = 0.005$), which declined across Waves 1–3 (slope $M = -0.04$, $p < 0.001$). To test whether optimal boundary separation significantly differed from actual boundary separation when participants are in or near middle adolescence, we re-centered the intercept at Wave 3. As predicted, teens' response styles shifted to be *less* cautious than optimal at Wave 3 (intercept $M = -0.04$, $p = 0.007$).

In contrast to results from the first piece of the growth model, the second intercept at Wave 7 did not significantly differ from zero (intercept $M = 0.02$, $p = 0.19$), and did not change across Waves 7–9 (slope $M = 0.003$, $p = 0.71$; see Figure S1b for the path diagram of this final model).

To summarize, teens were overly focused on accuracy over speed at Wave 1, but this pattern reversed by middle adolescence, such that teens were overly focused on speed over accuracy at Wave 3. Throughout late adolescence, participants engaged in response strategies that were nearly optimal.

Importantly, there was significant variance in deviation from optimal boundary separation at the first intercept ($\sigma^2 = 0.03$, $p = 0.001$) and the rate of change from Waves 1–3 ($\sigma^2 = 0.009$, $p = 0.04$), demonstrating that individual differences are present that can be predicted. Significant variance was also observed in the second intercept ($\sigma^2 = 0.03$, $p < 0.001$); although the degree of variance in the second slope term was similar to that of the first, it fell short of standard levels of statistical significance ($\sigma^2 = 0.005$, $p = 0.06$).

3.4 | Construct validation of deviation from optimal response caution

While the previous analyses reveal interesting developmental patterns of optimal response caution, it is important to demonstrate that the derived metrics have external validity. To that end, we compared deviation from optimal caution to measures of psychopathology and temperament.

3.5 | Waves 1–3

To simplify model estimation, validation models were run separately for each piece of the growth model described above (Waves 1–3; Waves 7–9). Including the set of psychopathology predictors improved model fit (relative to a model in which predictors were not estimated) for both the intercept ($\Delta\chi^2$ (6) = 16.40, $p = 0.01$) and slope ($\Delta\chi^2$ (6) = 13.98,

$p = 0.03$). As such, 12 individual parameters were evaluated (six predictors each for the intercept and slope). Participants with higher parent-reported internalizing symptoms on the CBCL at Wave 1 had higher initial levels, reflecting overly cautious responding ($\beta = 0.27$, $p < 0.01$), and there was a trend towards less change in deviation from optimality across Waves 1–3 ($\beta = 0.28$, $p = 0.08$). In contrast, greater inattention and conduct disorder symptoms were associated with lower intercept values (βs = −0.23, −0.24; ps = 0.02, 0.05 for inattention and conduct symptoms, respectively). Conduct disorder symptoms were also related to a steeper slope ($\beta = -0.55$, $p < 0.01$), indicating that teens exhibiting conduct problems in early adolescence showed a greater increase in their impulsive responding across time.

In contrast to results from the psychopathology predictors, including the set of temperament predictors did not improve model fit for either the intercept ($\Delta\chi^2$ (6) = 10.04, $p = 0.13$) or slope ($\Delta\chi^2$ (6) = 9.68, $p = 0.14$). Therefore, individual parameter estimates are not presented.

3.6 | Waves 7–9

Across late adolescence, including psychopathology or temperament predictors did not improve model fit in predicting either the intercept or slope ($\Delta\chi^2$s = 0.41 – 1.99, ps = 0.51 – 0.94).

4 | DISCUSSION

Developmental cognitive neuroscience models of adolescent risk behavior have come under criticism for their vague predictions and lack of specificity (Pfeifer & Allen, 2016). As the field moves towards enhancing specificity in model predictions and aligning analytic approaches with said predictions (Meisel et al., 2019), greater attention must also be paid to precision in measurement. Although investigations of how teens' response styles change across development and across contexts has clear relevance for testing theory, most work in this area has been limited in its use of performance metrics that confound processes of interest (e.g., speed –accuracy tradeoff) with processes of little theoretical relevance (e.g., motor response time or general task performance). The present study provides one example of how to overcome these problems. By using a computational model of decision-making that parses RT and accuracy into psychologically-distinct components, we were able to isolate response time that was due to how cautiously participants engaged with the task.

In contrast to previous studies, which often fail to find developmental differences in the impact of reward on behavioral tasks (Bjork et al., 2010; Geier & Luna, 2012; Geier et al., 2010; Paulsen et al., 2015), the current study did observe a differential effect of reward. The ability of reward to shift response style to emphasize speed over accuracy became greater as participants moved from early into middle adolescence, which is consistent with theoretical models of adolescent risk taking. A significant benefit of the diffusion modeling used in the current study is that it rules out plausible hypotheses that previous studies in this area could not. That is, it rules out the possibility that reward effects on task performance are driven by changes in processes that have far less theoretical significance, such as perceptual encoding or motor response speed.

At the same time, the magnitude of this differential reward effect across Waves 1–3 was fairly small. Perhaps the "true" effect is indeed small, in which case most previous studies would have been woefully underpowered to detect it. It is also possible that the points used as the reward manipulation in the present study were a relatively weak reinforcer, even though children exchanged their earned points for prizes. Though the points/prizes were clearly potent enough to impact performance, social rewards become increasingly salient in adolescence (Crone & Dahl, 2012; Foulkes & Blakemore, 2016), and peer presence influences teens' performance on laboratory tasks (Smith et al., 2014; Weigard et al., 2014). Thus, the pattern of reward effects observed here would likely be even more robust if the kinds of reinforcers that shape adolescents' everyday behaviors were used. It is also important to keep in mind that the decision-making process employed in the current study was simple and involved discriminating odd versus even numbers. A simple task with low-level cognitive demand was advantageous for the present purposes of evaluating how response caution shifts with reward because it minimizes the contribution of differences in cognitive abilities that would be present with more difficult tasks. Further, we focused on impulsive versus cautious *response style*, not impulsive or risky decision-making. That is, we evaluated how much information teens accumulate before they make a simple choice, rather than evaluating how teens weigh risks and benefits when making more complicated choices (such as in gambling tasks or the Balloon Analogue Risk Task). Extending this line of work to tasks that measure higher-order cognitive processes and risk-taking behavior of central relevance to adolescent development is an important direction for future research.

A major advantage of computational modeling is the ability to empirically estimate the tradeoff between speed and accuracy that is ideal for maximizing reward gains. This approach provides a more direct evaluation of developmental changes in rash or impulsive responding in rewarding contexts than relying on comparisons of different developmental groups. The present study's results are partially consistent with developmental theory.

Teens placed too much emphasis on accuracy in early adolescence, but this shifted to a maladaptive emphasis on speed over accuracy in middle adolescence. The maturational imbalance model, for example, would expect the peak risk period to occur around 15 years of age (Casey et al., 2008). The peak in rash responding in the current sample was observed when teens were approximately 14 years old, which is consistent with model predictions. It is important to note that we were unable to follow participants across ~ages 15, 16, and 17, which precludes any evaluation of changes occurring during this period. Thus, it is possible, and indeed likely, that the maladaptive emphasis on speed actually peaked sometime in the gap between the first waves and later waves before it returned to a more adaptive level around age 18.

The cognitive control system is thought to lag behind the reward systems until prefrontal areas are fully developed, when people are in their mid-20s (Casey, 2015; Shaw et al., 2008). A logical prediction of this differential development is that individuals in their late teens and early 20s may also engage in response styles that are excessively fast. We did not find evidence consistent with that prediction. Across late adolescence, participants' boundary separation was slightly, and non-significantly, more cautious than what was ideal for maximizing points. In other words, individuals were engaging in mostly optimal strategies by late adolescence. Given evidence that adults often adopt strategies that are overly cautious (Evans et al., 2019), an important avenue for future work is to continue following the development of response caution into adulthood. As cognitive control continues to increase beyond late adolescence, one possibility is that individuals may continue to shift toward greater caution in responding as a function of their improved self-regulatory capacities.

Due to the novelty of using simulations to quantify how much each person's response style deviated from what would be ideal, we evaluated theoretically relevant constructs to begin providing evidence of construct validity. In general, deviation from optimal response caution in early adolescence and change in optimal response caution across early to middle adolescence was most strongly associated with psychopathology. Out of the externalizing dimension, higher parent-reported inattentive ADHD and conduct disorder symptoms were linked to response styles that were overly focused on speed, and higher conduct disorder symptoms were further associated with greater shifts towards speed over accuracy across early to middle adolescence. Keep in mind that these relations were observed across method (computerized task vs. questionnaires) and across respondents (child performance vs. parent ratings). Previous work has generally failed to find differences in boundary separation between youth with and without ADHD (Fosco et al., 2017; Karalunas et al., 2014), which is often interpreted as between-group similarity in cautious versus impulsive response styles (Metin et al., 2013); yet, the dimensional associations in the current sample raise an interesting possibility. Youth with ADHD might not differ from their healthy peers in raw values of response caution, but they may differ in the degree to which their caution deviates from what is most adaptive for them. This hypothesis could be easily tested by computing optimal boundary separation for each individual and comparing the difference between actual and optimal boundary separation between groups. Of course, the key caveat to this approach is that the task must be administered in a reward or response cost context in order to evaluate what is optimal.

The associations of conduct disorder symptoms with both the intercept and slope suggest that our metric of deviation from optimal response caution may also prove a useful tool in studies of severe behavior problems in adolescence. Because conduct disorder behaviors encompass severe behavioral concerns that primarily fall outside the range of typical deviant adolescent behaviors (Nock et al., 2006), testing this hypothesis with a high-risk sample would provide important evidence to complement the current community sample results. Finally, although the present study was primarily centered around models of risk and externalizing behavior, we also found evidence for response caution's association with internalizing dimensions, suggesting that boundary separation may hold promise for investigations of longitudinal changes in depression and anxiety across early to middle adolescence.

In contrast to the findings for psychopathology, temperament ratings were surprisingly unrelated to one's deviation from optimal response caution. In addition to the relatively low reliability of the temperament scales that may have been a contributing factor, a key difference between the domains is the range of functioning they intend to capture. Psychopathology measures are adept at capturing the maladaptive or pathological end of the distribution, whereas temperament measures attempt to quantify the full spectrum. An important area for future research is to evaluate whether deviation from optimal boundary separation may be best-suited for studies of psychopathology/symptoms, rather than studies of normal variation in response caution.

Similarly, no associations between psychopathology or temperament and deviation from optimal boundary separation were present in late adolescence. On average, participants' actual boundary separation did not differ from what was optimal, so it is not surprising that adaptive performance did not relate to maladaptive outcomes. While replication is necessary, the differential pattern of associations between developmental periods indicates that the current approach may be most advantageous across the early-to-middle adolescent years.

5 | CONCLUSION

The present study was the first to employ computational modeling to clarify how reward affects behavioral strategies across adolescence, while ruling out rival explanations. Computational modeling provides multiple advantages over traditional behavioral performance metrics, and we hope that future research will utilize approaches that provide more precise measurement of constructs of central theoretical significance. We also introduced a novel metric to empirically derive the extent to which response speed became more or less adaptive across adolescence. We provided initial evidence that deviations from adaptive responding relate to both internalizing and externalizing psychopathology in early-to-middle adolescence, and we look forward to future work evaluating whether this novel metric is useful in investigations of other dimensions of psychopathology, as well as risk behaviors in adolescence.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to report.

DATA AVAILABILITY STATEMENT

Questionnaire data are publicly available through ICPSR (https://www.icpsr.umich.edu/web/ICPSR/studies/37620), and the E-prime task file is available on the developers' website (http://www.acsu.buffalo.edu/~program2/ubafdp/R_tasks.html). Task data are not publicly available due to limited resources stemming from financial constraints from the study's conclusion.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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