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SHORT REPORT

Cognitive control deployment is flexibly modulated by social value in early adolescence

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Abstract

Recent mechanistic models of cognitive control define the normative level of control deployment as a function of the effort cost of exerting control balanced against the reward that can be attained by exerting control. Despite these models explaining empirical findings in adults, prior literature has suggested that adolescents may not adaptively integrate value into estimates of how much cognitive control they should deploy. Moreover, much work in adolescent neurodevelopment casts social valuation processes as competing with, and in many cases overwhelming, cognitive control in adolescence. Here, we test whether social incentives can adaptively increase cognitive control. Adolescents (M_{age} = 14.64, 44 male, N = 87) completed an incentivized cognitive control task in which they could exert cognitive control to receive rewards on behalf of real peers who were rated by all peers in their school grade as being of either high- or low-status. Using Bayesian modeling, we find robust evidence that adolescents exert more cognitive control for high- relative to low-status peers. Moreover, we demonstrate that social incentives, irrespective of their high- or low-status, boost adolescent cognitive control above baseline control where no incentives are offered. Findings support the hypothesis that the cognitive control system in early adolescence is flexibly modulated by social value.

KEYWORDS

adolescence, Bayesian modeling, cognitive control, social incentives

1 | INTRODUCTION

A dominant framework used to explain how adolescent cognitive control differs from adult cognitive control casts social valuation processes as competing with, and in many cases, overwhelming the ability to exert cognitive control (e.g., Casey et al., 2008; Steinberg et al., 2008). However, recent advances on the computational architecture of cognitive control propose that all else equal, control should be engaged more when its exertion results in greater reward (Lieder et al., 2018; Shenhav et al., 2013). This normative principle is instantiated in a cognitive control system that must compare the inherent cost of exerting cognitive control to the potential reward one may receive as a result of exerting cognitive control. In other words, because exerting cognitive control requires effort, such effort is only estimated to be worth exerting when the rewards one will attain through exerting such effort outweigh the effort cost.

Investigating whether this principle of cognitive control holds in adolescence may be best approached by incentivizing cognitive control deployment with social rewards (Do et al., 2020). Indeed, past attempts to use monetary rewards to promote cognitive control deployment in adolescence have been mixed (Insel et al., 2017; Luna et al., 2013) perhaps due to heterogeneity in the subjective valuation of monetary incentives. By contrast, evidence suggests there is a sharp increase in the valuation of social rewards in adolescence relative to other developmental periods (Foulkes & Blakemore, 2016; Pfeifer & Berkman, 2018). Previous studies suggest social rewards, such as positive facial expressions, can bolster cognitive control performance above baseline levels without reward (Kohls et al., 2009) and to a larger extent in adolescents relative to adults (Cromheeke & Mueller, 2016). However, it remains unexamined whether varying the magnitude of a social incentive can adaptively modulate cognitive control deployment in adolescence, which is necessary to determine whether prior studies failing to show such effects are due to the domain of reward used to differentially incentivize cognitive control (i.e., monetary vs. social rewards), or whether adolescent cognitive control is insensitive to reward magnitude (e.g., Insel et al., 2017).

Adolescents value social status. High social status in adolescence comprises adolescents who are likable and popular, which is typically estimated by sociometrics assayed in school social networks (Prinstein, 2007). During adolescence, the motivation to enhance social status is uniquely prioritized over other goals (e.g., personal achievement; LaFontana & Cillessen, 2010), which can have long-term health consequences, particularly among adolescents with higher susceptibility to high-status relative to low-status peers (e.g., Prinstein et al., 2011). Adolescents are motivated to attain social status in various ways, such as conforming to high-status-peer behavior (e.g., Gommans et al., 2017; Helms et al., 2014). Once acquired, high social status provides several social benefits, such as having greater social influence over others (Sherman & Mehta, 2020), attaining high-quality friendships (Cillessen & Rose, 2005), and having greater success in pursuing romantic relationships (Simon et al., 2008). As a result, adolescents may view winning rewards for high-status peers as an opportunity to attain higher social status (LaFontana & Cillessen, 2010).

In the current study, we tested how social rewards—defined by high- and low-peer status—affect the deployment of congitive control in adolescents. In a computerized game, adolescents could earn points by engaging cognitive control, and such points incentivized performance because they determined the monetary value that would be given to their peers. Adolescents completed three rounds of the game, each with a different social reward value. They first completed a baseline round where performance was solely driven by intrinsic motivation and participants received no social reward. Including this baseline was crucial to determine whether cognitive control deployment in conditions with social rewards was greater than baseline levels of control where no incentives are offered. They then completed two counterbalanced rounds, one in which the points could be earned for a high-status peer, and one in which the points could be earned for a low-status peer based on adolescents' real-life social networks. We hypothesized that adolescents would exert greater cognitive control when they are socially rewarded for doing so, especially when the reward is deemed high relative to low value (i.e., high-status peer versus low-status peer), in line with computational theories on cognitive control deployment (e.g., Do et al., 2020; Shenhav et al., 2013).

RESEARCH HIGHLIGHTS

1. We demonstrate adolescents flexibly modulate cognitive control deployment according to social incentives
2. We validate a procedure to embed social status using sociometrics in a classic cognitive control task
3. We demonstrate that social incentives, regardless of value, boosts performance above baseline cognitive control deployment
4. We show these effects using robust Bayesian estimation

2 | METHODS AND MATERIALS

2.1 | Participants

Participants were recruited from a larger study of 873 6th and 7th graders from three public schools in the southeastern United States. Of this larger sample, 143 participants were enrolled in a longitudinal study comprising various lab-based tasks across the same study period. The current study reports data from the third wave of data collection, when participants were in the 8th and 9th grades. A total of 131 participants completed the experimental task. An additional 14 participants completed the study, but did not complete the experimental task (n = 6 moved schools and thus would not know the peers in the task; n = 7 had technical issues; n = 1 had time constraints). After excluding participants who failed manipulation checks (described below), our final sample included 87 participants (M_{age} = 14.64, SD_{age} = .60, $range_{age}$ = 13.39-16.28; 44 male). The sample was ethnically- and racially-diverse: 28.7% White (n = 25), 25.3% Black (n = 22), 34.5% Hispanic/Latinx (n = 30), 10.3% Multi-Racial (n = 9), 1.1% Other (n = 1). The mode of the highest maternal education level was some college (29.9%, n = 26), with a range of less than high school diploma (11.5%, n = 20) to beyond postbaccaulereate degree (7.9%, n = 7). In accordance with the university's Institutional Review Board, adolescent participants and their primary guardians provided written assent and consent, respectively.

2.2 | Peer status manipulation

To increase the motivational value of social incentives, high-status and low-status peers were identified from participants' real-life social networks. The social status of participants' peers was derived using classroom-administered peer nominations, collected annually in the larger sample (n = 873). Each participant received an alphabetized roster of all grade mates and were instructed to nominate an unlimited number of peers for four sociometric items commonly used to measure peer status: liked most ("the people in your grade you like the most"),

TABLE 1 Sociometrics of high-status and low-status peers

	High Status				Low Status			
	Female		Male		Female		Male	
	Likability	Popularity	Likability	Popularity	Likability	Popularity	Likability	Popularity
Grade 7								
School 1	1.08	1.48	.93	1.27	−1.11	−.87	−1.26	−1.53
School 2	1.73	1.38	1.06	1.13	−.92	−.82	−1.97	−1.27
School 3	.79	1.33	1.26	1.36	−.60	−.87	−1.76	−1.03
Grade 8								
School 1	1.58	1.24	.96	.75	−1.62	−1.25	−1.23	−1.96
School 2	.93	.88	1.29	1.02	−.56	−.92	−1.25	−1.13
School 3	1.17	.63	.67	1.18	−1.27	−.36	−.73	−.36

liked least ("the people in your grade you like the least"), most popular ("the people in your grade who are the most popular"), least popular ("the people in your grade who are the least popular").

In the current study, nominations received during the second wave were counted and standardized within each grade level of each school to reflect participants' most recent peer network. Based on prior work (e.g., Prinstein et al., 2003), preference-based peer status was computed as the standardized difference between standardized responses to the

liked-most and liked-least items, with higher scores reflecting higher likability among peers. Reputation-based peer status was computed as the standardized difference between standardized responses to the most-popular and least-popular items, with higher scores reflecting higher levels of perceived popularity among peers.

Participants were presented with high-status and low-status peers from their own school ($n = 3$) and grade (8th, 9th), and were matched to each participant's sex (male, female), resulting in 12 different versions of the task. High-status peers were selected based on being relatively high ($\geq$ 0.70 SD) in either likability or popularity scores, and were above the mean on both measures of peer status. Low-status peers were selected based on being relatively low ($\leq$ −0.70 SD) in either likability or popularity scores, and were below the mean on both measures of peer status. Sociometric scores for high-status and low-status peers were matched across the 12 different versions of the task (Table 1).

2.3 | Value-contingent cognitive control task

To measure value-contingent cognitive control, we employed an incentivized go/no-go task under high and low social rewards. Before the task, participants were informed that they could earn points for one of their peers based on their task performance. They were presented with 41 of their peers' yearbook photos and were told two peers would be selected at random. In reality, one high-status peer and one low-status peer were selected based on the sociometrics described above (Figure 1A). Participants were told that the peer who they earned the most points for would receive a gift card, such that the cumulative points earned for said peer would determine their overall monetary payout. However, no information was provided about how this peer would receive the gift card or about the exchange rate between points on the task and the monetary balance of the gift card. In reality, the peers did not receive the gift card. Note, we did not explicitly specify that the peer would be told the gift card came from the participant playing the task.

The go/no-go task was adapted from prior research examining high and low monetary stakes on cognitive control (Insel et al., 2017). The task included images of planets with craters as go targets and stripes as no-go targets. Participants were instructed to respond with a button press using the index finger of their dominant hand as quickly as possible for all go targets, but to withhold the button press for no-go targets (Figure 1). The targets, which consisted of 66% go targets and 33% no-go targets, were presented in a pseudorandom order for 500 ms with an intertrial interval (ITI) ranging from 1500 to 3500 ms ($M = 2400$ ms). Correct responses (i.e., pressing on go trials (hits) and inhibiting the button press on no-go trials (inhibition)) were rewarded with 20 points each, and incorrect responses (i.e., withholding button press on go trials (misses) and pressing on no-go trials (false alarms)) incurred a loss of 5 points each. Following each block of 21 targets, performance feedback displayed participants' cumulative earnings for the block for 4000 ms (see Figure 1B).

The task included three conditions: baseline, high social reward (i.e., high status peer), and low social reward (i.e., low status peer). Each condition was comprised of three consecutive blocks of 21 targets (trials) each, resulting in 63 trials per condition. Participants always completed the baseline condition first to assess optimal performance levels without external incentives and before expected declines over time (Telzer et al., 2017). In the baseline condition, participants were instructed to play three blocks of the task while earning as many points as they can, but the points would not earn a gift card. The high social reward and low social reward conditions were presented in a counterbalanced order following the baseline condition. Before each reward condition, participants viewed a picture of the corresponding peer (high status, low status), which served as a cue indicating the reward type of the subsequent trials.

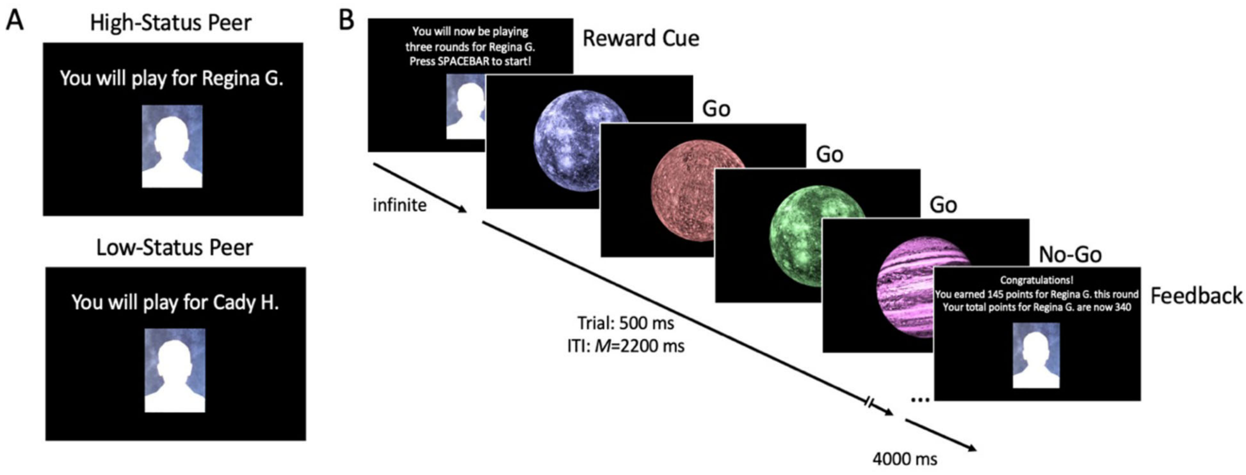

FIGURE 1 Schematic of value-contingent cognitive control task. (A) To increase the relevance of social rewards, high-status and low-status peers were identified from participants' real-life social networks. Social rewards were defined as prospective monetary earnings for the peers participants were playing for. (B) Participants viewed a high-status peer or low-status peer cue before making responses to three consecutive blocks of 21 targets each, which included 14 go (i.e., planets with craters) and 7 no-go (i.e., planets with stripes) targets. Correct responses were rewarded with 20 points each and incorrect responses incurred a loss of 5 points each, with cumulative earnings (i.e., feedback) displayed at the end of each block. Participants first played one round of the cognitive control task where no external incentive was offered in order to establish baseline performance. Subsequently, participants played two rounds, one for a high-status and one for a low-status peer, the order of which was counterbalanced across participants. ITI = intertrial interval

2.4 | Manipulation check

After the task, participants indicated whether or not they knew each of the two peers they played for during the task. Participants also rated the extent to which they liked and how popular they perceived each peer (1 = *not at all*, 2 = *a little bit*, 3 = *somewhat*, 4 = *very much*). To check our manipulation of peer status, we computed an average score of likability and popularity ratings for each of the two peers that participants played for in the task. Based on these manipulation checks, 42 participants were excluded from analyses either for reporting not knowing a peer they played for ($n = 33$) or rating the high-status peer as lower status than the low-status peer ($n = 9$). An additional two participants were excluded because they did not complete the manipulation check. Analyses were conducted on the remaining 87 participants, who all rated the high-status peer ($M = 3.04$, $SD = 0.66$) as higher status than the low-status peer ($M = 1.89$, $SD = 0.70$), $t(86) = 12.82$, $p < .001$.

2.5 | Data analysis plan

D-prime. We operationalized cognitive control as d-prime, a common metric of cognitive control (Tottenham, Hare & Casey, 2011), which was calculated as participants' sensitivity to engage behavior when a response was necessary (i.e., hits, or pressing on "go" trials) and withhold behavior when a response was not necessary (i.e., false alarms, or inhibiting an action during a "no-go" trial). D-prime was computed for all participants with the following equation: z(hits)-z(false alarms), where z(hits) and z(false alarms) are the z transforms of hit rate and false alarm, respectively (Macmillan & Creelman, 1991). If the hit rate was 1, it was converted to 0.99, and if the false alarm was 0, it was converted to 0.01 to ensure reasonable z-scores. D-prime was computed separately for each of the 3 conditions.

Bayesian regression model. We fit a Bayesian regression model to test our main hypothesis. The model fits parameters to quantify how cognitive control deployment differed across conditions (baseline, high status, low status) while accounting for effects of the overall grand mean and a subject-specific intercept that defines their performance marginalized over all conditions. We followed the recommendations of Kruschke (2014) to derive wide priors on the same scale as the data. Hypotheses are tested in a Bayesian estimation framework by defining a set of null values and comparing them to the observed parameters fit to the effect of interest. The null values are collectively referred to as the Region of Practical Equivalence (ROPE; Kruschke, 2018), as these values describe effects that are small enough to be of non-interest. The 95% highest density interval (HDI), describing the 95% most credible values for the effect, must be entirely separate from the ROPE in order for the effect to be deemed robustly supported. However, if the HDI is not entirely inside the ROPE, then one can quantify how much of the density is outside the ROPE. If most of the density is outside the ROPE, one can interpret this as trending towards an effect. We defined the ROPE below as 10% of the estimated standard deviation for relevant effects.

The regression predicted d-prime scores as a function of an overall group baseline, a subject-specific baseline parameter, a parameter defining the effect of the condition, and a covariate for the subject's own social status (computed as the average of likability and popularity sociometrics, as defined above). This linear combination of predictors was then inputted as the mean of a normal distribution used to predict d-prime scores, wherein the standard deviation represents

TABLE 2 Descriptive statistics

	Baseline M(SE)	Low-Status M(SE)	High-Status M(SE)
Full sample (N = 87)	1.81 (0.79)	2.03 (1.08)	2.24 (0.99)
Males (N = 44)	1.86 (0.78)	2.06 (1.25)	2.33 (1.05)
Females (N = 43)	1.75 (0.78)	2.01 (0.90)	2.15 (0.93)
Pearson Correlations	Baseline & Low-Status	Baseline & High-Status	High-status & Low-Status
	0.33	0.52	0.50

the random observational noise. This noise was defined by a uniform distribution bounded between 0 and the variance of the data, following recommendations by Kruschke (2014). The subject-level baseline parameter was drawn from a normal distribution with mean 0 and a standard deviation estimated hierarchically, wherein the hyperprior for the standard deviation was defined by the 'gammaShRaFromMode' function defined in Kruschke (2014). The condition and covariate effects were defined by unit normal priors. See Github code (https://github.com/psharp1289/social_planets) for the specific values of each prior.

A significant Bayesian effect is evidenced by the region of practical significance values (ROPE; black bar representing null effects) being entirely outside of the 95% most likely parameter values (called the Highest Density Interval or HDI; Kruschke, 2014). As such, the ROPE being outside the HDI is a decision criterion wherein one accepts the effect is supported (unlike traditional null hypothesis testing in typical practice wherein one rejects the null but cannot accept the alternative hypothesis). In all plots below, the black bar represents the ROPE, and the yellow bar the HDI. In addition to simple decision criteria, this Bayesian technique also estimates the degree of support for each possible magnitude of difference between conditions. As such, when most of the density is outside the ROPE (i.e., HDI and ROPE are slightly overlapping), we will denote this as a trending effect and delineate the exact portion of the posterior density falling outside the ROPE (Aczel et al., 2020; Kruschke, 2017).

To investigate whether or not condition effects were present for the high and low status conditions that were counterbalanced, we fit an additional Bayesian model to these data (i.e., we did not include baseline condition data). In doing so, we show that effects presented below hold, and that there were no order effects or interactive effects between order and condition (see Github for alternative model results).

Posteriors were estimated using Stan software wrapped in Python, pyStan. Only two parameters were changed from default settings: the alpha delta parameter was shifted to 0.9, and the max tree depth parameter was increased to 18, which reduced the amount of divergences. The default sampler in Stan is the Hamiltonian Monte Carlo (HMC) method, which is an instance of a Markov chain Monte Carlo (MCMC) sampler. We then converted all raw parameter estimates to new parameters via implementing the sum-to-zero constraint. This allows the baseline to be more interpretable as the grand mean (i.e., average across all trials and subjects), all main effect parameter estimates as deflections away from the grand mean, and interaction effects as deflections from the main effects. For main effects, we subtracted the posterior over one main effect from another (Kruschke, 2014).

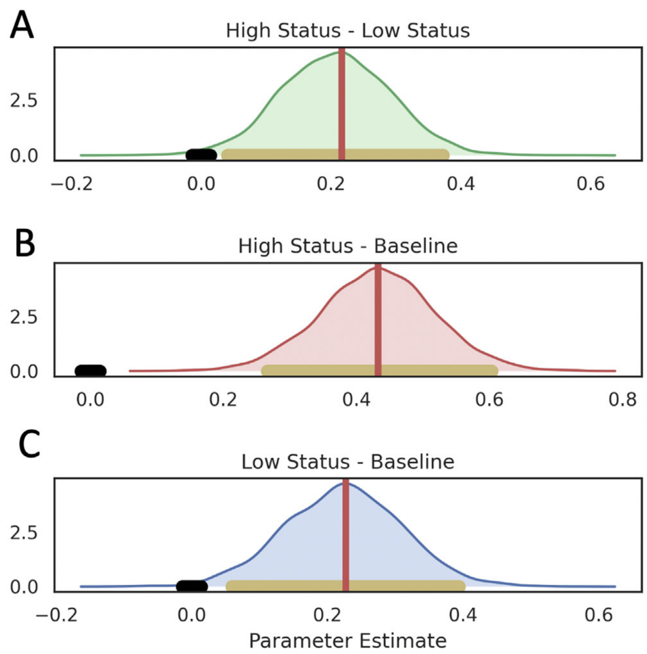

FIGURE 2 Main effects of condition. Posterior density plots over the difference between condition effects. The yellow bar defines the 95% HDI and the black bar defines the ROPE. The Y-axis represents the posterior density, and the X-axis is the difference in d-prime. The vertical red line marks the mode of the posterior.

3 | RESULTS

Descriptive statistics are presented in Table 2. Performance across the task was consistent across gender (the interaction of gender and task performance was non-significant). Moreover, performance across task conditions was significantly correlated within subjects (for all r, $p < .01$).

We predicted that adolescents will, on average, exert significantly greater control for high- versus low-status peers. Results (mode = 0.22, 95% CI: [0.04,0.37]) support this hypothesis (Figure 2a), such that on average, participants exerted more control when playing for high-status peers relative to low-status peers. We also found that social incentives boost control above baseline performance. That is, for high social status (mode = 0.43, 95% CI: [0.27,0.60], Figure 2b) and low social status (mode = 0.23, 95% CI: [0.06,0.39], Figure 2c), performance was significantly above baseline performance.

4 | DISCUSSION

The present study provides evidence that cognitive control deployment in early adolescence is flexibly deployed as a function of social reward value. We demonstrate that high social rewards can guide an increase of cognitive control relative to low social rewards and relative to baseline performance (i.e., no external incentives). This supports the hypothesis that rewards guide cognitive control deployment in adolescence (Shenhav et al., 2013), and demonstrates the utility of using social rewards to incentivize adolescent cognitive control deployment.

The present findings underscore how social reward processes and cognitive control can work in tandem, rather than in opposition, to promote adaptive behavior in early adolescence. Past evidence suggests that social valuation impinges on cognitive control, but these findings might be a product of goal conflict where adolescents seeking social approval by engaging in risk-taking must do so at the potential expense of winning money and doing well on the task (e.g., Chein et al., 2011). Social and non-social incentives may frequently be opposed to one another in daily life (Shulman et al., 2016), yet we demonstrate here that when incentives are aligned, increased social valuation promotes elevated cognitive control deployment. These findings have important implications for how positive social norms from high-status peers can be harnessed to alter adolescent behavior.

Our work cannot address the myriad reasons why inserting social stimuli (such as social observation, or the anticipation of social evaluation) into the context of performing cognitive control tasks may facilitate or impinge on adolescent cognitive control. The current project thus cannot resolve conflicting findings in prior work that inserts social stimuli in cognitive control tasks in a non-incentivizing way. For instance, prior work has shown that peer observation does not impact cognitive control performance (Smith et al., 2018), whereas the anticipation of monetary or social observation leads to diminished control when the cue used to signal inhibition is of positive valence (Breiner et al., 2018). We regard such work as investigating presumably related but different phenomena, including for instance fear of negative peer evaluation.

Primarily, our study sought to resolve how different levels of social rewards impact cognitive control when they are designed as performance-contingent incentives. Although prior work demonstrated adolescents increase cognitive control when incentivized with money (Luna et al., 2013), other work suggests adolescent cognitive control does not alter its level of deployment as a function of the magnitude of monetary incentives (Insel et al., 2017). In our study, we first demonstrated the importance of comparing mean differences across incentive conditions to a baseline. This allowed us to infer that even low-magnitude social incentives boost cognitive control above levels deployed due to intrinsic motivation and demand characteristics. Doing so improves the quantification of the influence of social rewards on cognitive control in adolescence. Most importantly, we demonstrated here that adolescents do indeed adaptively titrate cognitive control in line with incentives when they are social rewards. Slight differences in monetary incentives used in prior work (e.g., Insel et al., 2017) may not be different in terms of subjective value for adolescents. Here, we ensured there were significant differences in magnitude between social incentives via sociometrics gleaned from school based assessments and post-task self-report. This suggests that social rewards may serve a unique role in adolescence in motivating the deployment of effortful cognitive resources. This, in turn, supports an increasing body of work suggesting that valuation changes in adolescence can be channelled towards adaptive outcomes (e.g., Telzer et al., 2018). Our findings provide evidence that cognitive control may be more advanced in adolescence than suspected (i.e., it flexibly adjusts to incentivization) but requires developmentally-appropriate rewards to demonstrate such flexibility.

Of note, however, individuals may have strategically adjusted to the task (thus improving overall performance) in conditions with social incentives (that always occurred after an initial baseline measurement) which might confound our estimation of baseline performance with a lack of practice. Importantly, prior research suggests that cognitive performance declines across a Go Nogo task in adolescence (McCormick, Qu & Telzer, 2017). Moreover, our main finding contrasting performance between high and low social reward is not dependent on the baseline, and the order of these two conditions was counterbalanced. Nonetheless, future work should counterbalance the baseline condition order to verify conclusions drawn here regarding baseline performance, as well as include a non-social baseline where a participant earns money for their performance to examine whether social incentives are greater than personal monetary incentives.

Future work should additionally seek to disentangle reasons why adolescents are rewarded by winning money for peers they like to further elucidate the causal mechanisms explaining effects found here (Braams et al., 2014). This effort can be advanced in part by testing hypotheses regarding how computational models linking social valuation and cognitive control deployment are implemented in the developing brain. A possible neural implementation of this process centers on the relation between dopamine and cognitive effort. Recently, using a neuro-computational model of cognitive effort, it was shown that both dopamine baseline differences and dopamine-elevating medication increase the subjective valuing of benefits in the cost-benefit algorithm determining control deployment (Westbrook et al., 2020). Our findings are consistent with the hypothesis that social rewards increase the benefit (i.e., the reward valuation) component of the cognitive control estimation process that ultimately determines what degree of control is deployed. As such, our study was limited in its ability to not track trial-by-trial relationships between social reward and control deployment. Future work should endeavor to do so to validate further how computational models can explain the modulation of control via social rewards. Moreover, because we did not have a longitudinal sample, we cannot make claims about how these processes change over time. Indeed, it is possible that social rewards may be uniquely effective in modulating control during adolescence (Cromheeke & Mueller, 2016), but longitudinal designs are necessary to test this hypothesis.

In sum, the present findings suggest that social valuation is not in competition with cognitive control resources. Rather, what is essential to understanding how these processes interact is to determine whether the social reward is a consequence of engaging elevated control. Indeed, we show here that when social rewards are designed to be contingent on control, they flexibly increase cognitive control deployment in adolescence.

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CONFLICTS OF INTEREST

None of the authors have any competing interests

AUTHOR CONTRIBUTIONS

Paul B. Sharp, Kathy T. Do and Eva H. Telzer co-constructed hypotheses and the experiment. Paul B. Sharp conducted statistical analysis. Paul B. Sharp took the lead on writing the manuscript, with significant input and writing from Kathy T. Do and Eva H. Telzer. Paul B. Sharp, Kathy T. Do, Eva H. Telzer, Kristen A. Lindquist, and Mitchell J. Prinstein edited the manuscript.

DATA AVAILABILITY STATEMENT

Full scripts with de-identified data are available on GitHub at https://github.com/psharp1289/social_planets. Together, all results reported are reproducible from the code and data.

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REFERENCES

Braams, B. R., Peters, S., Peper, J. S., Güroğlu, B., & Crone, E. A. (2014). Gambling for self, friends, and antagonists: Differential contributions of affective and social brain regions on adolescent reward processing. *Neuroimage*, *100*, 281–289. https://doi.org/10.1016/j.neuroimage.2014.06.020]

Breiner, K., Li, A., Cohen, A. O., Steinberg, L., Bonnie, R. J., Scott, E. S., Taylor-Thompson, K., Rudolph, M. D., Chein, J., Richeson, J. A., Dellarco, D. V., Fair, D. A., Casey, B. J., & Galván A. (2018).Combined effects of peer presence, social cues, and rewards on cognitive control in adolescents. *Developmental Psychobiology*, *60*(3), 292–302. https://doi.org/10.1002/dev.21599

Casey, B. J., Getz, S., & Galvan, A. (2008). The adolescent brain. *Developmental Review*, *28*(1), 62–77 https://doi.org/10.1016/j.dr.2007.08.003

Chein, J., Albert, D., O'Brien, L., Uckert, K., & Steinberg, L. (2011). Peers increase adolescent risk taking by enhancing activity in the brain's reward circuitry. *Developmental Science*, *14*(2), F1–F10. https://doi.org/10.1111/j.1467-7687.2010.01035.x

Cillessen, A. H., & Rose, A. J. (2005). Understanding popularity in the peer system. *Current Directions in Psychological Science*, *14*(2), 102–105. https://doi.org/10.1111/j.0963-7214.2005.00343.x

Cromheeke, S., & Mueller, S. C. (2016). The power of a smile: Stronger working memory effects for happy faces in adolescents compared to adults. *Cognition and Emotion*, *30*(2), 288–301. https://doi.org/10.1080/02699931.2014.997196

Do, K. T., Sharp, P. B., & Telzer, E. H. (2020). Modernizing conceptions of valuation and cognitive-control deployment in adolescent risk taking. *Current Directions in Psychological Science*, *29*(1), 102–109. https://doi.org/10.1177/0963721419887361

Foulkes, L., & Blakemore, S. J. (2016). Is there heightened sensitivity to social reward in adolescence?. *Current opinion in neurobiology*, *40*, 81–85. https://doi.org/10.1016/j.conb.2016.06.016]

Gommans, R., Sandstrom, M. J., Stevens, G. W., ter Bogt, T. F., & Cillessen, A. H. (2017). Popularity, likeability, and peer conformity: Four field experiments. *Journal of Experimental Social Psychology*, *73*, 279–289 https://doi.org/10.1016/j.jesp.2017.10.001

Helms, S. W., Choukas-Bradley, S., Widman, L., Giletta, M., Cohen, G. L., & Prinstein, M. J. (2014). Adolescents misperceive and are influenced by high-status peers' health risk, deviant, and adaptive behavior. *Developmental Psychology*, *50*(12), 2697–2714. https://doi.org/10.1037/a0038178 PMID: 25365121

Insel, C., Kastman, E. K., Glenn, C. R., & Somerville, L. H. (2017). Development of corticostriatal connectivity constrains goal-directed behavior during adolescence. *Nature communications*, *8*(1), 1–10. https://doi.org/10.1038/s41467-017-01369-8

Kohls, G., Peltzer, J., Herpertz-Dahlmann, B., & Konrad, K. (2009). Differential effects of social and non-social reward on response inhibition in children and adolescents. *Developmental Science*, *12*(4), 614–625. https://doi.org/10.1111/j.1467-7687.2009.00816.x

Kruschke, J. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. New York, NY: Academic Press

Kruschke, J. K. (2018). Rejecting or accepting parameter values in Bayesian estimation. *Advances in Methods and Practices in Psychological Science*, *1*(2), 270–280. https://doi.org/10.1177/2515245918771304

LaFontana, K. M., & Cillessen, A. H. (2010). Developmental changes in the priority of perceived status in childhood and adolescence. *Social Development*, *19*(1), 130–147. https://doi.org/10.1111/j.1467-9507.2008.00522.x

Lieder, F., Shenhav, A., Musslick, S., & Griffiths, T. L. (2018). Rational metareasoning and the plasticity of cognitive control. *PLoS Computational Biology*, *14*(4), e1006043. https://doi.org/10.1371/journal.pcbi.1006043] PMID: 29694347

Luna, B., Paulsen, D. J., Padmanabhan, A., & Geier, C. (2013). The teenage brain: Cognitive control and motivation. *Current Directions in Psychological Science*, *22*(2), 94–100. https://doi.org/10.1177/0963721413478416

Macmillan, N. A., &:, & Creelman, C. D. (1991). *Detection theory: A user's guide*. Cambridge University Press

McCormick, E., Qu, Y., & Telzer, E. H. (2017). Activation in context: Differential conclusions drawn from cross-sectional and longitudinal analyses of adolescents' cognitive control-related neural activity. *Frontiers in Human Neuroscience*, *11*(141). https://doi.org/10.3389/fnhum.2017.00141] PMID: 28392763

Pfeifer, J. H., & Berkman, E. T. (2018). The development of self and identity in adolescence: Neural evidence and implications for a value-based choice perspective on motivated behavior. *Child Development Perspectives*, *12*(3), 158–164. https://doi.org/10.1111/cdep.12279

Prinstein, M. J. (2007). Assessment of adolescents' preference-and reputation-based peer status using sociometric experts. *Merrill-Palmer Quarterly (1982-)*, 243–261. https://doi.org/10.1353/mpq.2007.0013

Prinstein, M. J., Brechwald, W. A., & Cohen, G. L. (2011). Susceptibility to peer influence: Using a performance-based measure to identify adolescent males at heightened risk for deviant peer socialization.

Developmental psychology, *47*(4), 1167–1172. https://doi.org/10.1037/a0023274 PMID: 21463036

Prinstein, M. J., Meade, C. S., & Cohen, G. L. (2003). Adolescent oral sex, peer popularity, and perceptions of best friends' sexual behavior. *Journal of pediatric psychology*, *28*(4), 243–249. https://doi.org/10.1093/jpepsy/jsg012

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: An integrative theory of anterior cingulate cortex function. *Neuron*, *79*, 217–240. https://doi.org/10.1016/j.neuron.2013.07.007

Sherman, G. D., & Mehta, P. H. (2020). Stress, cortisol, and social hierarchy. *Current Opinion in Psychology*, *33*, 227–232. https://doi.org/10.1016/j.copsyc.2019.09.013

Shulman, E. P., Smith, A. R., Silva, K., Icenogle, G., Duell, N., Chein, J., & Steinberg, L. (2016). The dual systems model: Review, reappraisal, and reaffirmation. *Developmental cognitive neuroscience*, *17*, 103–117 https://doi.org/10.1016/j.dcn.2015.12.010

Simon, V. A., Aikins, J. W., & Prinstein, M. J. (2008). Romantic partner selection and socialization during early adolescence. *Child Development*, *79*(6), 1676–1692. https://doi.org/10.1111/j.1467-8624.2008.01218.x

Smith, A. R., Rosenbaum, G. M., Botdorf, M. A., Steinberg, L., & Chein, J. M. (2018). Peers influence adolescent reward processing, but not response inhibition. *Cognitive, Affective, & Behavioral Neuroscience*, *18*(2), 284–295.

Steinberg, L., Albert, D., Cauffman, E., Banich, M., Graham, S., & Woolard, J. (2008). Age differences in sensation seeking and impulsivity as indexed by behavior and selfreport: Evidence for a dual systems model. *Developmental Psychology*, *44*, 1764–1778. https://doi.org/10.1037/a0012955

Telzer, E. H., Qu, Y., & Lin, L. C. (2017). Neural processes underlying cultural differences in cognitive persistence. *Neuroimage*, *156*, 224–231. https://doi.org/10.1016/j.neuroimage.2017.05.034

Tottenham, N., Hare, T. A., & Casey, B. J. (2011). Behavioral assessment of emotion discrimination, emotion regulation, and cognitive control in childhood, adolescence, and adulthood. *Frontiers in Psychology*, *2*(39). https://doi.org/10.3389/fpsyg.2011.00039] PMID: 21716604

Westbrook, A., van den Bosch, R., Määttä, J. I., Hofmans, L., Papadopetraki, D., Cools, R., & Frank, M. J. (2020). Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. *Science*, *367*(6484), 1362–1366. https://doi.org/10.1126/science.aaz5891

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