American Psychological Association

Journal of Experimental Psychology: General

ISSN: 0096-3445

2021, Vol. 150, No. 1, 103–113
http://dx.doi.org/10.1037/xge0000769

How Adolescents and Adults Translate Motivational Value to Action: Age-Related Shifts in Strategic Physical Effort Exertion for Monetary Rewards

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Adults titrate the degree of physical effort they are willing to expend according to the magnitude of reward they expect to obtain, a process guided by incentive motivation. However, it remains unclear whether adolescents, who are undergoing normative developmental changes in cognitive and reward processing, translate incentive motivation into action in a way that is similarly tuned to reward value and economical in effort utilization. The present study adapted a classic physical effort paradigm to quantify age-related changes in motivation-based and strategic markers of effort exertion for monetary rewards from adolescence to early adulthood. One hundred three participants aged 12–23 years completed a task that involved exerting low or high amounts of physical effort, in the form of a hand grip, to earn low or high amounts of money. Adolescents and young adults exhibited highly similar incentive-modulated effort for reward according to measures of peak grip force and speed, suggesting that motivation for monetary reward is consistent across age. However, young adults expended energy more economically and strategically: Whereas adolescents were prone to exert excess physical effort beyond what was required to earn reward, young adults were more likely to strategically prepare before each grip phase and conserve energy by opting out of low reward trials. This work extends theoretical models of development of incentive-driven behavior by demonstrating that layered on similarity in motivational value for monetary reward, there are important differences in the way behavior is flexibly adjusted in the presence of reward from adolescence to young adulthood.

Keywords: adolescent, effort, motivation, reward, strategy

Supplemental materials: http://dx.doi.org/10.1037/xge0000769.supp

As humans navigate complex environments, it is crucial to make strategic and economical choices about potential actions to take. This process involves assessing the value of an action's outcome against the cost of taking that action. According to theories of incentive motivation, computations that weigh the costs and benefits of actions guide the allocation of effort devoted to obtaining a particular outcome (Berridge, 2004; Niv, Daw, Joel, & Dayan, 2007; Salamone, Correa, Farrar, Nunes, & Pardo, 2009). Thus, physical effort can serve as a measurable proxy for underlying motivational processes. In addition to invigorating effort allocation, incentive motivation can also guide strategic elements of behavioral output, such as choosing whether it is worthwhile to pursue a reward, and expending effort more efficiently while still obtaining desired outcomes (Tversky & Kahneman, 1981).

This article was published Online First June 4, 2020.

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Alexandra M. Rodman, Katherine E. Powers, and Leah H. Somerville designed the research; Alexandra M. Rodman, Katherine E. Powers, Abigail M. Stark, and Katherine E. Kabotyanski performed the research; Alexandra M. Rodman and Steven Worthington analyzed the data; Alexandra M. Rodman drafted the manuscript; Alexandra M. Rodman, Katherine E. Powers, Catherine Insel, Steven Worthington, and Leah H. Somerville provided critical comments and revisions; Erik K. Kastman provided technical support. All authors approved the final version of the manuscript for submission.

Versions of these data have been presented as a poster at the 2017 Flux Developmental Neuroscience Congress in Portland, Oregon, and as a talk at the 2019 New England Researchers in Decision Making: Cambridge, Massachusetts. A preprint has been made available at 10.31234/osf.io/zcw4s and data and code are available at https://osf.io/xj3hu/.

This work was supported by the APA Elizabeth Munsterberg Koppitz Fellowship to Alexandra M. Rodman and Leah H. Somerville and National Science Foundation CAREER award (BCS-1452530) to Leah H. Somerville. We are grateful to the Affective Neuroscience and Development Lab, Michelle Zhao, and Roula Kouvatas at Harvard University for helpful discussion and input. We acknowledge the statistical support provided by Patrick Mair.

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Seminal work in adults has demonstrated how behaviors shaped by incentive motivation track the value of a prospective reward (Klein-Flügge, Kennerley, Saraiva, Penny, & Bestmann, 2015; Kool, McGuire, Rosen, & Botvinick, 2010; Pessiglione et al., 2007; Schmidt, Lebreton, Cléry-Melin, Daunizeau, & Pessiglione, 2012; Shadmehr, Reppert, Summerside, Yoon, & Ahmed, 2019). Adults expend more physical and mental resources to obtain greater monetary rewards, as demonstrated in tasks that operationalize effort in terms of repeated button pressing (Treadway, Buckholtz, Schwartzman, Lambert, & Zald, 2009), speeded reaction times (Cools et al., 2005; Sedaghat-Nejad, Herzfeld, & Shadmehr, 2019), hand grip force (Kurniawan et al., 2010; Pessiglione et al., 2007; Schmidt et al., 2012), and higher working memory load (Krawczyk, Gazzaley, & D'Esposito, 2007; Schmidt et al., 2012). In addition, incentive motivation informs adults' strategic optimization of behaviors, such that anticipated rewards upregulate adults' behavioral control, as seen during tasks that require cognitive control over motor actions (Boehler, Schevernels, Hopf, Stoppel, & Krebs, 2014; Insel, Kastman, Glenn, & Somerville, 2017) or inform their choice of whether to pursue a reward in the first place, forgoing effortful actions for outcomes deemed low in value (Arulpragasam, Cooper, Nuutinen, & Treadway, 2018; Botvinick, Huffstetler, & McGuire, 2009; Hartmann, Hager, Tobler, & Kaiser, 2013; Klein-Flügge et al., 2015; Shenhav, Botvinick, & Cohen, 2013).

Although adults use reward value to strategically guide effort allocation, it remains unclear how reward value informs motivated action during adolescence, a phase of the life span when a host of reward-related processes are undergoing normative developmental change that distinctly influences cognition and behavior (Somerville, Jones, & Casey, 2010). On the one hand, adolescents exhibit hyperresponsivity to reward cues relative to children and adults (Galván, 2013; Spear, 2011), which has been associated with disrupted response inhibition (Davidow, Sheridan, et al., 2019; Somerville, Hare, & Casey, 2011), and greater brain activation in the ventral striatum, a region involved in reward value computations (Braams, van Duijvenvoorde, Peper, & Crone, 2015; Ernst et al., 2005; Silverman, Jedd, & Luciana, 2015; Van Leijenhorst et al., 2010; but see Sherman, Steinberg, & Chein, 2018). Based on these findings, we might expect adolescents to show exaggerated effort exertion to obtain rewards relative to adults.

On the other hand, recent work has demonstrated that adolescents are continuing to refine the use of incentives to guide goal-directed actions. While adolescents notice, understand, and wish to obtain rewards, normative development imposes limitations on the adaptive use of reward cues to guide moment-to-moment actions (Davidow, Insel, & Somerville, 2018). For example, when rewarded for accurate performance on a response inhibition task, adolescents did not improve performance as adults did (Insel et al., 2017). Along these lines, we may expect the processes that strategically translate motivational value to effortful action to emerge during adolescence. To resolve these competing alternative models, we used an incentivized physical effort paradigm that indexes and dissociates motivation-based and strategic markers of effort exertion for monetary rewards.

We also sought to empirically scrutinize the widely held assumption that the same amount of money holds similar value to individuals of different ages. In developmental research paradigms, monetary outcomes are commonly used as reward cues to probe concurrent cognitive processes (e.g., decision-making, impulse control), often without consideration as to whether it is valued in a fundamentally equivalent way across these ages. Adolescents and adults have dramatically different levels of access to money and spend money in different ways in daily life (Alhabeeb, 1996). Although some research has quantified subjective, self-reported affective responses to monetary reward in developmental samples, this work has yielded inconsistent results. Some studies show that adolescents report greater positive affect than adults after winning an equivalent amount of money (Ernst et al., 2005), whereas other studies have found no age-related differences in subjective report of valence or arousal to monetary outcomes (Bjork et al., 2004; Insel et al., 2017; Insel & Somerville, 2018). The current study can lend more objective clarity to whether money holds the same motivational value to adolescents and adults, operationalized here as the relative difference in incentive-modulated behavior to obtain higher and lower amounts of money.

Method

Overview

Participants spanning early adolescence through young adulthood (N = 103; 12–23 years of age) were instructed to exert force on (i.e., squeeze) a hand dynamometer to obtain low or high amounts of money ($0.05 and $0.75); see Figure 1A. Trial difficulty was set to either low or high effort and was customized to a threshold of 40% or 80% of individually calibrated maximum grip strength to account for baseline differences in individual strength.

The effect of reward on physical effort was examined by extracting several distinct measurements of the grip timeseries, analyzed at the trial level (Figure 1B). *Incentive-guided effort exertion* was quantified using two measures: (a) the *peak grip force* exerted and (b) the *speed* at which participants reached threshold, wherein high reward outcomes are expected to provoke greater strength and speed output than low reward outcomes. These behavioral measures comprise response vigor to obtain reward, a proxy indicator of incentive motivation (Niv et al., 2007; Salamone et al., 2009). To quantify the *strategic optimization of effort exertion,* we extracted three measures: (a) the degree of excess force exerted after obtaining reward as indicative of less optimal exertion (i.e., *perseveration*), (b) the delay to initiating the grip phase by button press (i.e., *preparation*), and (c) the rate of trial noncompletion, or opting out of trials altogether, reasoning that individuals may choose to *opt-out* of trials requiring effort for low reward outcomes.

Participants

One hundred nine healthy individuals were recruited from the greater Boston area. Exclusion criteria included history of a neurological disorder and current psychiatric disorder. Six participants were excluded from final analyses for noncompliance during the calibration (N = 2; ages 19.48 and 22.78), squeezing for the entire trial against instruction (N = 2; ages 20.77 and 20.88), disbelief the task was real (N = 1; age 21.98), and exhibiting difficulty comprehending task instructions and purpose (N = 1; age 21.63). The remaining 103 participants were included in data analyses.

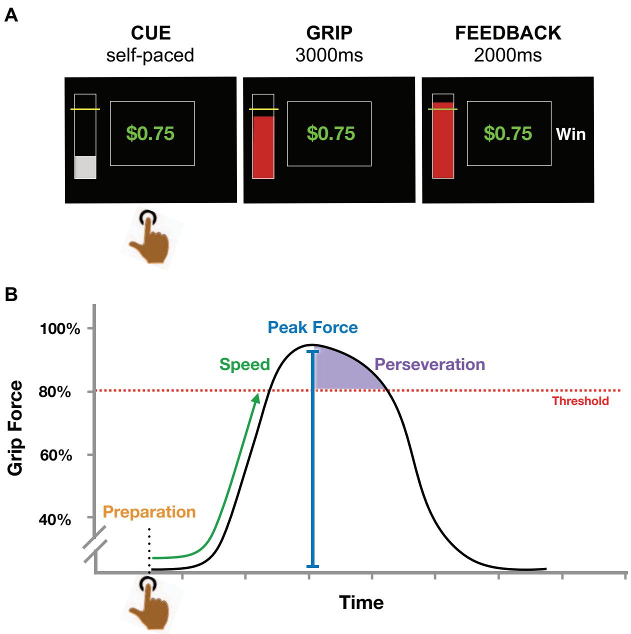

Figure 1. Schematic representation of the grip force task and output measures. (A) Participants viewed a cue indicating the difficulty of the trial (yellow line) and the monetary outcome of successful effort exertion for that trial. Participants pressed a button when they were ready to initiate the grip phase. When squeezing the hand dynamometer, physical effort was displayed in real time by the height of the red bar. If their physical effort reached the yellow threshold line (40% for easy, 80% for hard as shown above), the yellow line turned green and participants received feedback indicating they earned the amount of money displayed. If they did not reach the threshold in 3,000 ms, the trial would end, and participants received feedback indicating they did not receive the monetary outcome. (B) Schematic of grip force timeseries data for an individual trial. We quantified *incentive-guided effort exertion* as peak force exerted during the trial (blue) and speed to reach the threshold (green), with greater force and speed indicating greater effort. We quantified *strategic optimization of effort exertion* as the perseverative post-peak effort exerted after the outcome was obtained (purple), the amount of time spent preparing before the button press initiating the grip phase (orange; panel A, left) and the rate of opting out of attempting to obtain the reward (not shown; see the Method section).

Published data on effort exertion for monetary reward across development was not available to conduct an a priori power analysis. Thus, we ensured that the sample size was sufficiently powered to detect small to medium effects by linear regression (i.e., parameter estimate $\beta > .30$; Cohen, 1988). A power analysis using the package *pwr* in R (Champely et al., 2018) suggested that 85 participants would be required to detect an effect of this size at 80% power. We recruited an additional 20 participants because of the developmental population.

Participants were aged 12.03–23.77 years (M = 18.15, SD = 3.54; Figure S1 in the online supplemental materials) and 53.40% male. There was no evidence that the distribution of age varied systematically across gender (independent t test: $t[102] = -0.311$, p = .756). Participants' ethnic and racial diversity was broadly representative of the local community of Cambridge and Boston, MA with 58.5% Caucasian, 17.0% Asian, 9.4% African American, and 8.5% Multiracial (1.9% unreported). Participants were recruited through online forums such as Craigslist, advertising in local newspapers, and flyers. Participants provided informed written consent or assent, and parents or legal guardians of minor participants gave written permission for their child's participation. The Committee for the Protection of Human Subjects at Harvard University approved all research procedures.

Equipment

The grip force task was presented using PsychoPy (v1.84), which interfaced with Biopac, Inc. (Goleta, CA) hand dynamometer hardware. Grip force was recorded using a hand dynamometer (Biopac TSD121B-MRI) made of two molded plastic cylinders that, when squeezed, compress an air tube. Air compression was converted into voltage proportional to the exerted force by a transducer. This value was sent to a Biopac DA100C module and converted from analog to digital signal using a custom-built 3.5-mm breakout board connected to a National Instruments USB-6009 multifunction IO box. This digital signal was sampled at 60 Hz and used a continuous input to PsychoPy to provide real-time visual feedback during the task, wherein participants saw a vertical bar on the screen rise and fall proportionally to their grip force (Figure 1A). Participants were instructed to use their dominant hand, which was stabilized using Velcro for the duration of the task to maintain uniform hand configuration.

Maximum Grip Calibration

At the start of the study session, participants completed a stepwise calibration procedure to titrate the relative difficulty of trials to each individual's hand strength. During the calibration, participants repeatedly attempted to reach the top of a vertical bar representing sequentially higher grip levels on each successive attempt until they were no longer able to reach the threshold and their maximum grip strength was recorded. This maximum grip value was used to calibrate the task thresholds proportionally to participants' strength (easy threshold: 40% of maximum; hard threshold: 80% of maximum), as in prior work (Kurniawan et al., 2010). This calibration procedure was repeated immediately following the task to quantify possible overall fatigue effects. One participant (aged 23.73) was not included in this analysis for failure to complete the second maximum grip calibration. Although maximum grip calibration values were treated as a linear covariate in all regression models, it is possible that this parameter has nonlinear properties.

To test whether there were task-related fatigue effects that varied with age, we computed a linear mixed-effects robust regression with predictors of time (dummy variable representing pre- or posttask), continuous linear age, and their interaction, with y intercept as a random effect grouped by participant and maximum grip calibration as the dependent variable. As expected, maximum grip calibration differed across age with grip strength increasing with age (B = 0.180, SE = 0.046, 95% CI [0.090, 0.270], $p < .05$). However, participants did not exhibit a significant difference in grip strength pre- to posttask (B = −0.062, SE = 0.057, 95% CI [−0.174, 0.049], $p > .100$), and pre–post change in maximum grip calibration did not interact significantly with age (B = −0.027, SE = 0.016, 95% CI [−0.059, 0.004], $p > .100$). These results indicate that (a) the acquired data are unlikely to be contaminated by fatigue-related behavior changes and (b) whatever fatigue effects are present are not systematically different across age. Although short-term within-trial fatigue effects are not accounted for in these tests, they are mitigated by the within-subjects design and cannot fully explain any age by reward interactions. In addition, we included trial number as a nuisance covariate in all subsequent analyses to account for any subtle, or unmeasured effects of fatigue on task performance.

Task Procedure

Each trial began with a display showing the vertical grip progress bar on the left side of the screen with a yellow line indicating the effort required for that trial (easy/40% or hard/80%), and the monetary reward at stake ($0.05 or $0.75) presented in the middle of the screen, all of which remained visible for the duration of the trial (Figure 1A, left). Consistent with previous studies implementing this task (Kurniawan et al., 2010; Schmidt et al., 2012), we included low and high levels of difficulty in the design to induce a psychological context in which effort is made salient by varying it across trials. As in prior work, participants were instructed to press the space bar when they were ready to begin gripping to isolate the execution phase of the timeseries (Kurniawan et al., 2010). During the grip phase (the 3,000 ms immediately following pressing the space bar), participants applied force to the hand dynamometer, and if the progress bar exceeded the yellow threshold, it turned green to indicate the participant had reached the threshold and earned the payout (Figure 1A, middle). The feedback phase (2,000 ms) reiterated whether the participant successfully crossed the threshold with positive trials displaying *Win!* on the right side of the screen and unsuccessful trials showing nothing (Figure 1A, right).

The task contained 32 trials in total, equally split across the four conditions (easy $0.05, easy $0.75, hard $0.05, hard $0.75). A relatively small number of trials was used to mitigate fatigue effects. After the task, participants received performance-contingent bonus payouts in cash which totaled the sum of all successful trials. All participants completed an initial practice version of the task to ensure comprehension.

Outcome Measures

Timeseries data acquired in the grip force task permit the isolation of several different components of the overall grip response. We computed the standard measure of physical effort exertion—*peak grip force*—defined for each trial as the highest intensity of grip force exerted (excluding opt-out trials), expressed in units of percent of maximum grip calibration ($N = 3200$, 97% of trials). Second, we measured the *speed of effort exertion* operationalized as time (in milliseconds from the start of the grip phase) to reach the threshold for each successful trial ($N = 3{,}125$, 95% of trials). Together, peak grip force and speed reflect the response vigor exerted during pursuit of the rewarding outcome, as a readout of incentive motivation (Niv et al., 2007; Salamone et al., 2009).

We computed three additional measures of task performance that index more strategic aspects of motivational process. First, we measured the degree of excess force exerted after obtaining the reward. This measure, termed *perseveration,* was defined for each successful trial as the area under the curve of the grip timeseries, from the point participants reached the peak force until their force exertion dropped below that trial's threshold, excluding trials where grip force was already above threshold at the start or end of the trial ($N = 3069$, 93% of trials). Second, we measured latency of grip phase initiation. This measure, termed *preparation,* was defined for each trial as the duration in milliseconds from the start of the trial (cue phase; Figure 1A, left) to when participants indicated readiness for the grip phase with a button press (all 3296 trials included in analyses). Finally, although participants were instructed to grip for each trial, initial data inspection revealed a small proportion of trials for which participants did not attempt to approach the threshold, suggesting that they chose not to exert force on that trial. We thus quantified and tallied these *opt-out* trials in an exploratory fashion as a possible index of strategic conservation of energy (all 3296 trials included in analyses). For easy trials, a trial was considered an opt-out if the grip force did not exceed half the distance to the threshold, or 20%. For hard trials, a trial was tallied as an opt-out if the grip force did not exceed the average peak grip force for easy trials, or 56.94%. Control analyses were conducted to ensure these measures were not redundant or requiring multivariate analyses (see Table S4 in the online supplemental materials).

Analytical Approach

Group analyses queried for the effects of reward (low, high), participant age, and their interactions on the five dependent measures: peak grip force, speed, perseveration, preparation, and opt-out frequency. Linear robust (for continuous data) or logistic (for binary data) mixed effects regressions were computed for each measure with reward (low vs. high), age, and their interaction as key predictors of interest, with *y*-intercept as a random effect grouped by participant. We also included the following covariates in each model: trial difficulty level, trial number (to account for potential fatigue effects), and maximum grip strength calibration (to account for any residual influence of each individual's grip strength on dependent measures). Below, we report on reward-dependent results of interest, whereas full model results are presented in Table 1.

We inspected the distributions of the residuals of each regression model and conducted a natural log transform to correct for non-normality of residuals for dependent variables speed, perseveration, and preparation. Separate linear mixed-effects robust regression analyses were conducted for each continuous dependent measure using the *rlmer* function of the *robustlmm* package (Koller, 2016) in R (v 3.5.2). Opt-out trials were examined by logistic mixed-effects regression using the *glmer* function in the *lmer4* package (Bates, 2007). Robust regression uses a procedure that accounts for outliers at both trial and participant levels to reduce undue influence on parameter estimates (Koller, 2016). This procedure fits models with a nested iterative reweighting algorithm to down-weight residuals and random effects that are especially influential (see Koller, 2016 for more information). We derived Wald confidence intervals for the fixed effect parameter estimates, which were used to calculate p values reported as $p < .05$ or $p > .05$ (e.g., 95% CI for $p < .05$, 99.9% CI for $p < .001$). All parameter estimates are reported in unstandardized units (B).

Table 1
Full Results for Linear Age Regression Models of Each Dependent Variable

Dependent variable	Covariate	*B*	*SE*	95% CI lower	95% CI upper	*p*
Peak grip force	Reward	1.653	0.227	1.209	2.098	$<.001^{***}$
	Age	−0.236	0.144	−0.519	0.046	$>.05$
	Age × Reward	0.080	0.064	−0.046	0.206	$>.05$
	Difficulty	30.527	0.228	30.081	30.973	$<.001^{***}$
	Max calibration	−0.572	0.344	−1.247	0.102	$>.05$
	Trial number	−0.098	0.012	−0.122	−0.074	$<.001^{***}$
Speed (log transformed)	Reward	−0.045	0.010	−0.065	−0.025	$<.001^{***}$
	Age	−0.001	0.009	−0.020	0.017	$>.05$
	Age × Reward	−0.004	0.003	−0.009	0.002	$>.05$
	Difficulty	0.439	0.010	0.419	0.459	$<.001^{***}$
	Max calibration	0.022	0.022	−0.022	0.065	$>.05$
	Trial number	−0.002	0.001	−0.003	−0.001	$<.001^{***}$
Perseveration (log transformed)	Reward	0.205	0.032	0.142	0.268	$<.001^{***}$
	Age	−0.054	0.018	−0.089	−0.018	$<.001^{***}$
	Age × Reward	0.020	0.009	0.002	0.038	$<.03^{*}$
	Difficulty	−0.868	0.033	−0.931	−0.804	$<.001^{***}$
	Max calibration	−0.108	0.043	−0.192	−0.023	$<.02^{*}$
	Trial number	−0.020	0.002	−0.024	−0.017	$<.001^{***}$
Preparation (log transformed)	Reward	0.026	0.017	−0.007	0.060	$>.05$
	Age	−0.015	0.011	−0.036	0.006	$>.05$
	Age × Reward	0.011	0.005	0.001	0.020	$<.025^{*}$
	Difficulty	0.147	0.017	0.113	0.180	$<.001^{***}$
	Max calibration	0.053	0.025	0.004	0.103	$<.04^{*}$
	Trial number	−0.006	0.001	−0.008	−0.004	$<.001^{***}$
Opt-out	Reward	−3.910	0.616	−5.293	−2.823	$<.001^{***}$
	Age	0.003	0.224	−0.439	0.515	$>.05$
	Age × Reward	−0.440	0.154	−0.771	−0.151	$<.005^{**}$
	Difficulty	8.270	1.378	5.982	11.414	$<.001^{***}$
	Max calibration	−0.145	0.452	−1.195	0.770	$>.05$
	Trial number	0.105	0.022	0.063	0.150	$<.001^{***}$

Note. B = unstandardized coefficient; SE = standard error of coefficient.
$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

Age effects were queried using two age functions, linear (steady gain or loss) and quadratic (adolescent-peaking or dipping) effects, by inputting polynomial age terms as orthogonalized covariates of interest using the R function *poly*. This approach allows for dissociation of age-related patterns of change (Rodman, Powers, & Somerville, 2017), where hyperresponsiveness to rewards during adolescence would result in quadratic age effects and steady acquisition of reward-guided action would result in linear age effects. As such, linear age models included a linear age predictor and quadratic age models included both linear and quadratic age predictors. Because calculation of traditional model fit statistics was not possible for robust mixed-effects regressions, we computed all age models and assessed the significance of age terms. Quadratic age terms (simple and interaction effects with reward) were never significantly associated with dependent variables, and as such, we report linear age effects in the main text. Quadratic age model results can be found in Table S1 in the online supplemental materials.

We focus this report on simple and incentive-dependent (reward-by-age interaction) effects of linear age to test for overall age-related change in behavior in the context of reward (e.g., more exaggerated behavior overall, regardless of reward level), as well as relative differences in behavioral scaling with increasing incentives (e.g., the extent of behavioral enhancement for high compared with low rewards). When linear age effects were nonsignificant, suggesting a lack of relationship between age and the dependent measures, we used Bayesian methods to derive probability estimates assessing the strength of evidence supporting a null age pattern (Bürkner, 2017; Kruschke, 2011), which guided the appropriate inferences to draw from nonsignificant effects. See the online supplemental materials for details on the implementation of the Bayesian null inference tests. Analyses in R code and participant data are available online at https://osf.io/xj3hu/.

Results

Incentive-Guided Effort Exertion

Peak grip force. As expected, participants exerted greater peak grip force during high reward trials (M = 72.84%, SD = 17.61%) compared with low reward trials (M = 70.42%, SD = 17.66%; simple effect of reward: B = 1.653, SE = 0.227, 95% CI [1.203, 2.093], $p < .001$), collapsed across levels of difficulty. This indicates that high reward elicited greater effort exertion, validating that this measure is sensitive to differences in reward-based incentive motivation. See Table S2 in the online supplemental materials for descriptive statistics further separated by reward and difficulty.

Next, key analyses tested whether reward-dependent scaling in peak grip force exertion varied across age. Findings revealed no significant interaction effects between reward and age (B = 0.080, SE = 0.064, 95% CI [−0.046, 0.206], p > .200) or simple effect of age (B = −0.236, SE = 0.144, 95% CI [−0.519, 0.046], p > .100). See Table 1 for full results of the linear age models.

Bayesian parameter estimation was used to guide inference on the likelihood that the observed null age effects reflected a true underlying null distribution using a region of practical equivalence (ROPE) approach (Kruschke, 2011). See the online supplemental materials for additional details about the null inference test methodology. Results showed that the majority of posterior estimates fell within narrow ROPE intervals considered effectively zero (see Table S3 in the online supplemental materials); for reference, 70% of the simple age parameter distribution fell between ±0.3% and 83% of the age by reward interaction parameter distribution fell between ±0.1% peak grip force change. We interpret these findings as strong evidence supporting a true underlying null effect of age on peak grip force for high reward compared with low reward outcomes (Figure 2A).

Speed. We examined grip speed as the latency between initiating the grip force phase and reaching the threshold. Participants were faster to reach the threshold for high reward trials (M = 824 ms, SD = 429 ms) compared with low reward trials (M = 839 ms, SD = 421 ms; B = −0.045, SE = 0.010, 95% CI [−0.065, −0.025], p < .001), collapsed across levels of difficulty. Once again, high reward elicited speeded responses, which supports the use of this measure as an index of incentive-modulated response vigor.

When examining the effects of age, results revealed no significant interaction between reward and age (B = −0.004, SE = 0.003, 95% CI [−0.009, 0.002], p > .150) and no simple effect of age (B = −0.001, SE = 0.009, 95% CI [−0.020, 0.017], p > .800). These findings indicate that participants exerted greater response vigor for high reward compared with low reward outcomes and this did not differ significantly across age (Figure 2B).

Once again, results of the ROPE null inference tests showed that the majority of posterior estimates fell within narrow ROPE intervals considered effectively zero (see Table S3 in the online supplemental materials); for reference, 50% of the simple age parameter distribution fell between ±4 ms of speed change and 57% of the age by reward interaction parameter distribution fell between ±3 ms speed change, which we interpret as a high likelihood of a true null effect of age on grip speed. See the online supplemental materials for more information about the null inference test and Table 1 for full results.

Taken together, the grip force and speed results suggest that monetary reward cues motivate incentive-driven physical effort similarly across adolescence and early adulthood.

Strategic Optimization of Effort Exertion

Perseveration. Perseveration, characterized as the force maintained *after* obtaining the reward, was assessed to determine whether economical use of energy differed by high versus low reward or across age. Participants exhibited reward-dependent perseveration, with greater postreward effort expended for high reward trials (M = 0.604, SD = 1.256) compared with low reward trials (M = 0.479, SD = 0.839; B = 0.205, SE = 0.032, 95% CI [0.142, 0.268], p < .001) collapsed across levels of difficulty, even though this effort expenditure did not influence success on the trial.

Age-related tests of participants' perseveration revealed a significant simple effect of age (B = −0.054, SE = 0.018, 95% CI [−0.089, −0.018], p < .001) qualified by a significant interaction between reward and age (B = 0.020, SE = 0.009, 95% CI [0.002, 0.038], p < .03), such that with linearly increasing age, participants disengaged their physical effort more efficiently after obtaining the reward, especially for low reward trials (see Figure 3). These findings indicate that with increasing age, participants ex-

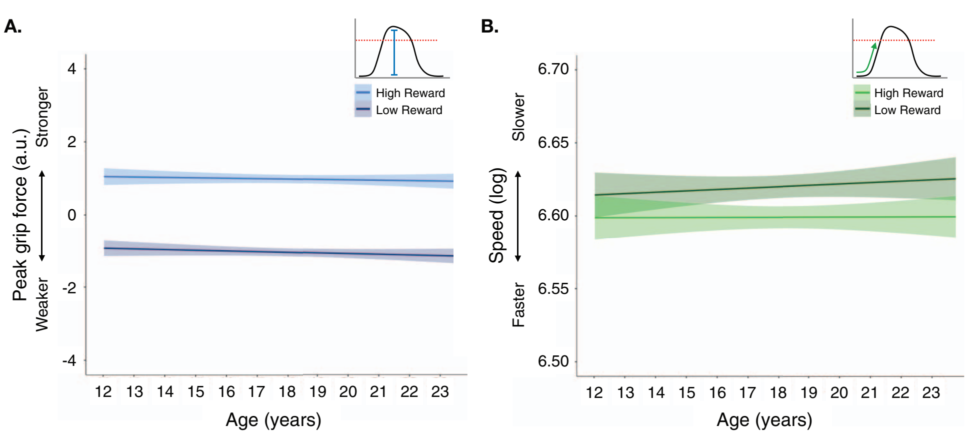

Figure 2. Incentive-driven effort exertion is age-invariant. (A) Participants exerted greater peak grip force for high (light blue) compared with low reward trials (dark blue), a behavioral pattern that was consistent across age. The y axis depicts peak grip force (proportion of maximum grip calibration) residualized for trial difficulty and maximum grip calibration, given its uniquely strong association with these parameters, resulting in arbitrary units. (B) Participants were faster to reach the threshold for high (light green) compared with low reward trials (dark green), a pattern that was age-invariant. The y axis depicts log transform of Speed (measured in ms). Data are collapsed across difficulty levels. Trends display linear fit of the data and shading indicates standard error of the mean (SEM).

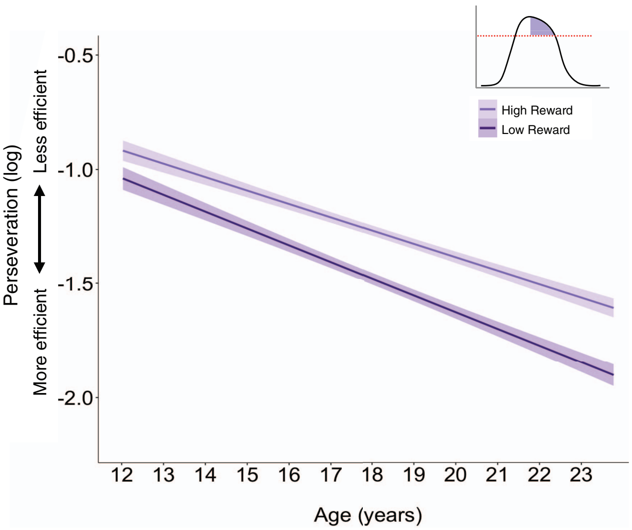

Figure 3. Age-related effects on perseverative grip force in the context of reward. Graph shows greater perseveration for high compared with low rewards and a negative relationship between linear age and perseveration. Younger participants showed a greater tendency for perseveration during both low (dark purple) and high reward trials (light purple) when compared with older participants, especially for low reward trials. The *y* axis depicts log-transform of perseveration (measured as AUC). Data are collapsed across difficulty levels. Trends display linear fit of the data and shading indicates standard error of the mean (*SEM*).

hibited more strategic and economical use of force, especially when reward outcomes were low, whereas younger adolescents were more prone to overexerting physical force for both high and low reward outcomes. See Table 1 for full model results.

Preparation. Button press response times indexed the latency of participants' readiness to initiate the grip phase, which was of interest based on the logic that individuals might spend more time strategically preparing for trials that held particular value to them. Response times were positively associated with increased peak grip force (see the online supplemental materials), suggesting it served an instrumental purpose. Thus, we interpret increased latency as a proxy for strategic *preparation* for effort exertion.

Although descriptive statistics indicated that participants were slower to initiate the grip phase before high reward (M = 1,369 ms, SD = 1,383 ms) compared with low reward trials (M = 1,280 ms, SD = 1,139 ms) collapsed across levels of difficulty, this effect was not significant (B = 0.026, SE = 0.017, 95% CI [−0.007, 0.060], $p > .050$). However, this was qualified by a significant age by reward interaction described below.

Findings revealed a significant interaction between reward and age (B = 0.011, SE = 0.005, 95% CI [0.001, 0.020], $p < .025$), wherein with increasing age, participants exhibited longer preparation time for high relative to low reward trials (Figure 4A). There was no simple effect of age on preparation (B = −0.015, SE = 0.011, 95% CI [−0.036, 0.006], $p > .200$). Once again, older participants exhibited evidence of value-dependent preparation that emerged during late adolescence into young adulthood. See Table 1 for full model results.

Opt-Out Trials

Opt-out trials were defined as trials in which participants did not attempt to obtain the reward, which may reflect reward-dependent choice behavior (see the Method section for quantification of opt-out trials). For example, individuals may choose to conserve energy on trials that require effort for low reward. Participants opted-out significantly more often on low reward trials (M = 4.92%, SD = 21.62%) than on high reward trials (M = 0.91%, SD = 9.50%; B = −3.910, SE = 0.616, 95% CI [−5.293, −2.823], $p < .001$) collapsed across levels of difficulty, demonstrating less willingness to work for low reward trials. Moreover, this occurred almost exclusively for hard trials (M = 5.70%, SD = 23.20%), with participants opting out of only two

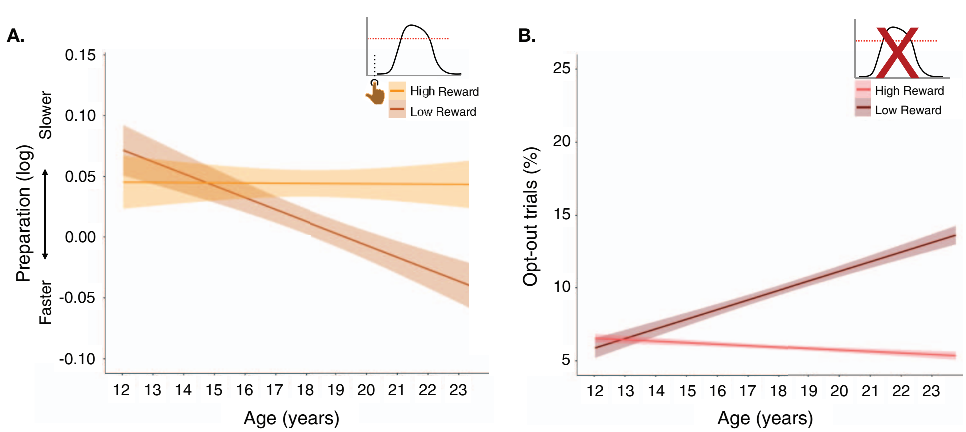

Figure 4. Strategic action for low versus high reward across age. (A) Graph shows reward interacts with age during pregrip phase preparation (i.e., delay before initiating a trial), where the tendency to differentiate between low and high rewards by taking longer to prepare for high reward outcomes emerges with age into adulthood. The *y* axis shows log-transform of preparation. (B) Graph shows interaction between linear age and reward on tendency to opt-out of trials. Older participants demonstrated more strategic behavior, opting out of more trials that required effort for low reward (dark red). Data are collapsed across difficulty levels. Trends display linear fit of the data and shading indicates *SEM*.

easy trials total (M = 0.12%, SD = 3.48%; B = 8.270, SE = 1.379, 95% CI [5.982, 11.414], $p < .001$).

Key analyses queried whether opt-out trials varied by age, and we found a significant interaction between reward and age (B = −0.440, SE = 0.154, 95% CI [−0.771, −0.151], p = .004). The interaction revealed that with increasing age, individuals opted out of more trials that were low reward, strategically preserving energy (Figure 4B). There was no simple effect of age on opt-out behavior (B = 0.003, SE = 0.224, 95% CI [−0.439, 0.515], p = .988). See Table 1 for full model results.

Discussion

In the current study, we adapted a well-validated willingness-to-work paradigm (Pessiglione et al., 2007) to examine behavioral outcomes associated with physical effort exertion to obtain reward. We found that participants spanning adolescence to young adulthood similarly expended greater response vigor, quantified by peak grip force and speed, to obtain \$0.75 compared with \$0.05 rewards. However, adolescents did not conserve energy as optimally as adults did, and were less strategic in their choices: Adolescents showed a heightened tendency to maintain grip force unnecessarily after obtaining reward, whereas adults used reward value to more effectively guide preparatory responding and choices to opt-out of low reward trials altogether. Together, these findings show that the invigoration of effort with increasing reward value extends to adolescent samples. However, there are key age-related gains in strategic effort allocation from adolescence to young adulthood. Although the motivational value of money appears similar throughout adolescence and into young adulthood, the ability to flexibly optimize behavior and conserve energy in the context of reward continues to refine throughout adolescence into young adulthood.

Adolescents and adults exerted similar levels of increasing effort for higher incentives, as demonstrated by greater peak grip force and faster speed. This invigorating impact of incentive value on effortful work output is in line with prior research in adults examining physical and mental effort, wherein adults show greater strength output, faster speed, and repeated attempts to obtain higher rewards (Pessiglione et al., 2007; Schmidt et al., 2012; Treadway et al., 2009). Extending this work to a developmental investigation is an important step in disentangling the different components of motivated behavior development. Using a task that is capable of dissociating motivational and strategic processes, we demonstrated that adolescents and adults exhibit comparable incentive-driven effort exertion for monetary reward. Bayesian methods strengthened the interpretation of this null age finding by demonstrating the high likelihood that the observed effects represent a true underlying null distribution. This finding is broadly consistent with one prior study showing similar speed in response to reward cues between adolescents and young adults (Bjork et al., 2004).

Although participants across the age range exhibited comparable incentive-driven response vigor, the extent to which they strategically employed effort varied by age. Adults showed more swift, economical disengagement after obtaining reward, thereby conserving energy, especially for low reward trials, whereas adolescents tended to maintain grip force exertion longer than necessary. These findings are in line with previous studies that have found adolescents exhibit less strategic exploratory behavior than adults in the context of increasing rewards (Somerville et al., 2017). Likewise, research using animal models has shown that, compared with adult rats, adolescent rats exerted more effort in reward-paired lever pressing, even when food delivery was no longer contingent on lever pressing (DeAngeli, Miller, Meyer, & Bucci, 2017). In humans, when task performance benefits from flexible deployment of motor action in response to rewards, such as an incentivized go–no-go task, adults typically enhance cognitive control with increasing rewards, but adolescents are less likely to adjust behavior according to incentive value (Insel et al., 2017). Taken together, these findings indicate that adolescence is a key phase of continued growth in using reward information to guide the flexible optimization of behavior (Davidow et al., 2018).

We also examined the delay before initiating the grip phase as an additional measure of strategic behavior. When compared with adolescents, adults exhibited more evidence of strategic preparation, taking more time before high effort (see Table 1) or high reward trials relative to low. This preparatory behavior was positively associated with peak grip force performance and not related to the tendency to opt-out of trials, implying that it served an instrumental purpose in performance execution rather than decision-making processes (see analyses in the online supplemental materials). These results are in line with previous work wherein participants showed a greater delay before hard compared with easy trials in an experimental context (Kurniawan et al., 2010), and in field studies of elite athletes where increased latency before golf swings predicted better outcomes (Crews & Boutcher, 1986). Our findings demonstrated that the tendency to factor in trial reward value and difficulty into preparation time increased with age, another indication that strategic reward-dependent behaviors continue to develop with age.

Although participants were instructed to complete all trials, there was a small proportion of trials participants did not complete. Though few trials were opted-out overall, this behavior occurred in an age-dependent and strategic manner. Opt-out behavior occurred almost exclusively for hard trials and more often for trials of low reward. And although opt-out behavior was observed in participants across the entire age range, older participants tended to opt-out of trials more often than younger participants, especially when reward value was low relative to high. The possibility that factors unrelated to the task, such as motivation to comply with experimental instructions, contributed to the opt-out behavior reported here cannot be ruled out. However, the findings from this measure closely converge across other indices of strategic behavior (i.e., perseveration, preparation), which cannot be explained by compliance-related behavior, consistent with its characterization as a strategic process. These findings are aligned with the general principle that as effortful cost required to obtain a reward increases, the value of the reward is discounted (Botvinick et al., 2009; Hartmann et al., 2013; Klein-Flügge et al., 2015), where adults choose to engage in trials that are lower in effort when reward is equal (Arulpragasam et al., 2018; Kurniawan et al., 2010). Our findings build upon this previous research by providing evidence that this strategic behavior was less evident in younger participants and are further supported by a recent study that found adults choose lower effort trials more often than adolescents (Sullivan-Toole, DePasque, Holt-Gosselin, & Galván, 2019). Therefore, these findings suggest that the strategic conservation of energy becomes fine-tuned during the transition from adolescence to adulthood.

Recent work has leveraged advances in computational modeling to enhance our understanding of the component processes that drive cost–benefit analyses and incentive-guided behavior (Klein-Flügge et al., 2015; Niv et al., 2007; Shadmehr et al., 2019). We used an experimental design utilizing a physical effort task to objectively measure incentive motivation in participants spanning adolescence to young adulthood. The current task was benchmarked on classic studies of motivation-related responses to reward and effort (Kurniawan et al., 2010; Pessiglione et al., 2007) to examine how high and low motivational value states invigorate behavior across adolescence into adulthood. However, the current task design was not optimized for formal mathematical modeling. Future work could bridge these approaches by including design features, such as probabilistic outcomes and incremental levels of reward and effort, to permit computational modeling to assess reinforcement learning or how reward and effort signals are integrated (e.g., effort discounting valuation curves). This is a critical next step to further characterizing these findings, both in terms of reward learning and whether effects are differentially driven by reward value signals or effortful cost signaling.

In all, our findings demonstrate that different facets of incentive motivation are differentially impacted by reward value across development. The long-discussed adolescent elevation in reward-related behaviors (Somerville et al., 2010) does not appear to be caused by differences in the motivational value of money, as demonstrated in the current study using objective measures. This finding is meaningful, because many studies exploring reward responses across development probe reward and cognitive processes using equivalent monetary reward cues, assuming that these cues are valued equivalently across age. These findings provide key experimental evidence to support the continued use of money as a reward cue in experimental research with participants spanning adolescence to adulthood.

At the same time, these findings suggest that there are important age-related differences in the way behavior is flexibly adjusted in the presence of reward. Increases in strategic approaches to the task with age from adolescence to adulthood result in the optimization of effort exertion and the conservation of energy. One possible explanation is that adolescents are continuing to fine-tune the extent to which value cues in the environment guide strategic goal-directed behavior (Davidow et al., 2018). Future work should extend this experimental approach to other domains of value, including social reward. Given the importance of social belonging during adolescence (Somerville, 2013), it stands to reason that peer evaluation is of particular value during this phase of the life span.

Conclusions

The current study examined age-related changes in incentive-driven exertion of physical effort for monetary reward. We show equivalency in incentive-dependent response vigor, whereas the incentive-dependent optimization of strategic effort exertion for reward targets has a protracted emergence throughout adolescence into young adulthood. This work extends theoretical models of the development of incentive-driven behavior by demonstrating that layered on similarity in motivational value for monetary reward, there are important differences in the way behavior is flexibly adjusted in the pursuit of reward from adolescence to young adulthood.

Context of the Research

Every day, we make value judgments that weigh the potential benefits of an outcome against the cost of obtaining the outcome. Although well studied in adults, research has yet to identify whether adolescents, who are undergoing normative developmental changes in cognitive and reward processing, show differential motivational value for rewards compared with adults. On the one hand, adolescents may be more motivated by rewards more than adults. On the other hand, adolescents may be similarly motivated by rewards as much as adults, but the use of motivational value for prospective rewards to update their actions may change with age. Here, we implemented a classic physical effort paradigm to measure how hard individuals of different ages would work for different levels of reward outcomes. We found that younger adolescents are willing to work just as hard as adults to obtain high rewards. However, adults are more strategic about when and how they optimize effort exertion, and they preserve energy for worthwhile outcomes. Thus, the age-related differences in reward-related behavior that are often observed in the transition from adolescence to adulthood may reflect differences in the ability to use incentives to strategically allocate effort, rather than differences in the motivational value of rewards. This work challenges the prevailing theory that adolescents simply value rewards more and has implications for public health concerns such as risk-taking behavior common to adolescence.

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Received August 27, 2019
Revision received March 4, 2020
Accepted March 4, 2020 ■