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Characterizing Age-Related Change in Learning the Value of Cognitive Effort

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Adults often titrate the degree of their cognitive effort in an economical manner: they "think hard" when the reward benefits of a task exceed its difficulty costs. Nonetheless, it remains to be seen whether and how children and adolescents adjust their cognitive effort according to multiple cues about its worthwhileness, including in novel environments where these cues must be learned through experience. Given that the processing of incentive and demand information changes with age, the present study examines participants' (primary experiment $N_{\text{usable}} = 150$, secondary experiment $N_{\text{usable}} = 150$, ages 10–20 years) performance across two task-switching paradigms that manipulated the rewards offered for, and the difficulty of, engaging cognitive effort. In the primary experiment, reward cues were instructed but difficulty cues were learnable. In the secondary experiment, the reward and difficulty cues were both instructed, eliminating learning demands and effectively making the task easier. The primary experiment revealed that although less difficult contexts promoted greater accuracy at the group level, the regulation of cognitive effort according to higher and lower incentives emerged with age. Especially early in the task, older participants achieved greater accuracy for higher incentives. Younger participants, unexpectedly, achieved greater accuracy for lower incentives and adolescents performed similarly for each reward level. Nonetheless, participants of all ages self-reported trying their hardest for higher incentives, but only adults translated this aim into action. The secondary experiment revealed that in an overall easier task environment, cognitive effort did not become increasingly economical with age. Taken together, this pattern of findings suggests that different sources and amounts of information, and the conditions they are presented in, shape learning the value of cognitive effort from late childhood to early adulthood.

Public Significance Statement

While adults have been shown to weigh instructed reward benefits and learnable difficulty costs when deciding how hard they try on a given task, less is known about how children and adolescents use these information sources to adaptively allocate their effort. Addressing this gap, here we demonstrate that, with age, individuals increasingly rely on information that tells them about how demanding a task will be and what incentives they can earn for performing well. However, children through adults self-report trying harder when greater rewards are at stake. These results reveal that the way multiple sources of information are presented guides how much individuals try in different ways across age, which has important implications for further applied education research that aims to design developmentally appropriate materials.

Keywords: adolescence, development, cognitive effort, learning, reward

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To efficiently navigate their environments, individuals of all ages must decide which tasks merit the expenditure of cognitive effort. For example, if Jane is a student who cannot complete all the homework that she is assigned and yet wants to earn the best marks that she can, Jane should determine which assignments are most worthwhile. Worthwhile assignments are low in difficulty (e.g., Jane's math homework is less demanding than her history homework) and high in potential reward (e.g., Jane's math homework contributes to a larger percentage of her final grade than her history homework). Like Jane, adults do not maximize their effort all the time because cognitive processing resources are limited (Kool et al., 2017; Shenhav et al., 2017, 2021; Westbrook & Braver, 2015). Rather, adults typically engage in cost–benefit analyses to guide their effort exertion, deploying effort when its reward benefits exceed its difficulty costs (Frömer et al., 2021; Grahek et al., 2023; Otto et al., 2022; Westbrook et al., 2019). Notably, adults even learn the information necessary to perform cost–benefit analyses in novel environments (Bustamante et al., 2021; Grahek et al., 2023; Otto et al., 2022). Still, it is important to understand how age-related changes in the arbitration between difficulty and reward information shape how cognitive effort is allocated across development. The economical allocation of cognitive effort is a case study of a broader topic of interest: how does strategic, goal-directed behavior change from childhood to adulthood? Clarifying how different types of information are used to promote efficient cognitive effort exertion sheds light on how individuals come to pursue adaptive outcomes through adolescence.

Children, adolescents, and adults may react variably to simultaneous sources of information. Prior research demonstrates that when multiple information streams are available, *which* streams and *how many* streams are called upon to make decisions and learn from those choices change with age. Namely, children and adolescents seem to rely on proximal reward information more than their adult counterparts (Decker et al., 2015, 2016; Nussenbaum et al., 2020; Palminteri et al., 2016; Potter et al., 2017). On the other hand, adults have access to an array of sophisticated choice strategies that allow them to exploit more sources of information (Lieder & Griffiths, 2017). This developing ability, to access a diverse array of decision-making strategies, is important for facilitating the increasingly flexible judgments required of adults (Jacobs & Klaczynski, 2002; Munakata et al., 2012).

Although children and adolescents utilize reward information that is immediately available to a greater extent in their choices, adults titrate their goal-directed behavior for different degrees (Cohen et al., 2022; Insel et al., 2017; Rodman et al., 2021; Störmer et al., 2014) and different rates (Devine et al., 2021) of incentive opportunities more than younger individuals. This may be because adults are better at calibrating their learning to the reinforcement statistics of their environments (Nussenbaum & Hartley, 2019) and assigning values to their goals (Davidow et al., 2018). Since making reward-maximizing decisions, and learning from them, increase through adolescence (Hartley & Somerville, 2015; Wilbrecht & Davidow, 2024), we first hypothesize that adults will, economically, invest more cognitive effort when higher incentives are at stake, while children and adolescents will not modulate their cognitive effort according to incentive magnitude.

Cost–benefit analyses that guide cognitive effort exertion involve more than just reward information. Individuals should also heed information about how demanding a task will be when deciding how hard to try. Sometimes, the difficulty level of a task must be learned through repeated experiences. Ganesan and Steinbeis (2021) tested the use of demand information in children 5–11 years through high- and low-difficulty cognitive control tasks. After acclimating to the demands required of each task, participants chose which they would like to complete and the response time for their decision was recorded. Throughout the sample, participants took longer to choose the high-difficulty task, suggesting that children as young as 5 years are cognizant of cognitive effort costs (Ganesan & Steinbeis, 2021). However, *detecting* a difficulty signal is not the same as *leveraging* it to adjust one's cognitive effort for the situation at hand. Indeed, whether children 5–11 years use information about task demands to guide their cognitive effort depends on their metacognitive insight into the difficulty of a task: in Ganesan and Steinbeis (2021), if children accurately estimated how well they could perform in the high-difficulty task, then they were more likely to choose it. Perhaps, such metacognitive insights allowed children to gauge whether the cognitive effort required of the task matched their abilities and act appropriately.

Further evidence for difficulty information shaping cost–benefit analyses in adults more than in children and adolescents is seen in studies of proactive versus reactive control. Manipulating proactive and reactive control has been used previously to change how easy or hard a task will be: deploying proactive control (sustained and anticipatory goal maintenance) can make succeeding in cognitive tasks more attainable than would be possible by deploying reactive control (transient and stimulus-driven goal reactivation; Braver, 2012). Proactive control strategies ease moment-to-moment processing and improve performance. Therefore, proactive versus reactive control research offers an indirect window into the effects of difficulty on cognitive effort during development. While younger children may be *aware* of proactive and reactive control manipulations, *engaging* demand-reducing proactive control to improve cognitive task performance continues to emerge into older childhood, adolescence, and adulthood (Chatham et al., 2009; Chevalier et al., 2015; Martinez et al., 2018; Niebaum et al., 2019, 2021). Therefore, the application of difficulty information to cognitive effort decisions is thought to develop through adolescence, and age variability may be especially apparent in motivational contexts (Wilbrecht & Davidow, 2024).

Taken together, the lines of work described above indicate that increases in age are associated with enhancements in the capacity to monitor cognitive effort expenditure, an aptitude thought to anchor on metacognition (Chevalier & Blaye, 2016), as well as enhancements in the employment of proactive control to promote success during forthcoming cognitive tasks. Because metacognitive abilities improve through adolescence (Chevalier, 2015; Weil et al., 2013) and proactive versus reactive control modes become selected more adaptively during the same period, we expect that—in addition to changing incentives for cognitive effort—changing difficulty levels of a task will impact how much cognitive effort is devoted to it (to perform well) differently across age. Namely, our second hypothesis predicts that adults will economically withdraw their cognitive effort when task demands are relatively high, while children and adolescents will not regulate their cognitive effort according to varying degrees of demand. As for reward information, difficulty information will shape cognitive effort decision making increasingly with age.

So far, we have established the fairly *respective* roles that reward and difficulty information may play in the cost–benefit analyses that direct cognitive effort exertion in children, adolescents, and adults. However, existing research suggests that how reward and difficulty information are *incorporated* to guide cognitive and physical effort investment also varies considerably with age (Rodman et al., 2021; Veselic et al., 2021). For instance, across multiple, cued difficulty levels, adults but not adolescents alter their effort according to the magnitude of reward they know to be at stake (Rodman et al., 2021; Veselic et al., 2021). Nonetheless, a gap remains in our knowledge about how children through adults navigate this goal-directed behavior: how do individuals modulate their cognitive effort not just according to multiple sources of information, but to sources of information that are not immediately available and instead are *learned over time*?

To characterize this modulatory process, we employ a child-friendly task-switching paradigm that manipulates incentivized and demanding cognitive control (including block design elements adapted from Otto et al., 2022). In a primary experiment, to make estimating the value of cognitive effort tractable in children, we allow one source of information to be accessible and force one source of information to be acquirable. For this paradigm, reward information is explicitly instructed but difficulty information must be learned through experience. In testing task-switching performance for each incentive and demand manipulation, we predict that participants of all ages will *detect* difficulty information on its own. However, our third hypothesis is that adults, more than children and adolescents, will *integrate* and *leverage* these information sources: the incentive and demand cues will combine to guide adults toward efficient cognitive effort exertion over time. Concretely, a reward and difficulty interaction will emerge between the beginning and ending blocks of the task for older participants but not for younger participants, such that adults eventually perform highest in easy, rewarding conditions and lowest in hard, unrewarding conditions. For completeness, a secondary experiment administered in a separate sample probes the role of learning versus instructing information by, instead, cueing difficulty explicitly. Our fourth hypothesis expects that age-related changes in efficient cognitive effort exertion will be even more pronounced when this information source does not need to be learned through experience. Finally, we also measure participants' views of their task-switching performance for each manipulation, and our fifth hypothesis is that metacognitive accuracy will improve through adolescence. Ultimately, we predict that both lines of analyses will reveal that the titration of cognitive effort according to instructed reward and learnable difficulty cues becomes more economical from late childhood to early adulthood (hypotheses one to four) as metacognitive awareness of cognitive effort grows (hypothesis five).

Method

Participants

One hundred fifty-two individuals ages 10–20 years participated in this online study. They were evenly distributed across age and parent/guardian- or self-reported gender ($M_{\text{age}} = 15.49$ years, $SD_{\text{age}} = 3.17$ years; 79 participants reported their gender as feminine, 68 participants reported their gender as masculine, three participants reported that their gender was not captured by the previous options; Supplemental Figure S1). From a list of races, 11.33% identified as Asian, 6.67% as Black/African American, 60.67% as White/Caucasian, and 21.33% reported that their race was not captured by the previous options. From a list of ethnicities, 12.00% identified as Hispanic while 88.00% did not. Participants were contacted from a database of families and through other means of community recruitment, then screened for exclusion criteria. Participants must have been living in the United States at the time of the study. Additionally, participants (and for minors, their parents/guardians) were excluded if they did not have corrected-to-normal visual acuity, were not fluent in English, or had cognitive impairments limiting their ability to consent/assent or execute the task. Participants were also excluded if they were current users of psychotropic medications; had current learning disabilities; had autism, attention deficit hyperactivity disorder, movement disorders, or other major health problems; had current psychiatric or neurological illness diagnoses (except adjustment disorder); and if they did not have corrected-to-normal audition. Participants must have completed over 90% of the practice phase and learning task (described below) to be included in the present sample. If a participant failed to do so, another age- and gender-matched participant was recruited to take their place. One participant was excluded from all analyses for failing to respond to more than 90% of practice trials (age = 20.55 years) and one participant was excluded for failing to respond to more than 90% of learning trials (age = 18.39 years). The remaining 150 participants were included in the primary data analyses. Speed outlier trials (trials for which a participant's reaction time was greater than three standard deviations from their mean reaction time) were excluded from all analyses; this criterion applied to 1.64% of trials. One additional participant was excluded from the post-task rating analyses (described below) because they closed the study prematurely (age = 10.59 years).

The sample size exceeds that of adult-only work implementing a similar, blocked task-switching paradigm (Otto et al., 2022; 83 participants), as well as prior research examining reward-modulated physical effort engagement from early adolescence to young adulthood (Rodman et al., 2021; 103 participants ages 12–23 years). A traditional a priori power analysis was not conducted because, to our knowledge, no extant studies have examined—in our age range—how cognitive effort is moderated by coinciding reward and difficulty information across time.

Participants were paid $20.00 for an hour for their time and were eligible to receive up to $15.20 in performance-based bonus payments. Compensation was administered through a gift card of the participant's choosing. Prior to the present study, participants were invited to partake in another project from our laboratory and were compensated separately. During that testing session, participants provided informed consent/assent and parents/guardians of minors gave their permission for both studies. All data collection practices were approved by the Committee on the Use of Human Subjects at Harvard University.

Online Testing Environment

Participants completed the study from home, on a laptop or desktop computer, using a Google Chrome web browser. To make the study accessible to as many participants as possible, participants could complete the experiment asynchronously at any time over the course of a week, as long as they did so in one sitting. Parents/guardians of minor participants were repeatedly instructed not to intervene during the study (e.g., Supplemental Figure S2). The study was hosted on Qualtrics and Pavlovia, and the task-switching paradigm was programmed using PsychoPy (Version 2021.2.3; Peirce et al., 2019), which offered the requisite precision for the behavioral measures of interest (Supplemental Methods). All data were de-identified on these platforms. Nearly every participant finished the entire experiment in under 40 min.

Ahead of the experiment, participants completed the matrix reasoning subtest of the Wechsler Abbreviated Scale of Intelligence (Wechsler, 2011) to evaluate whether there was unbalanced cognitive ability across the sample as a product of age-related sampling biases or random chance. We did not find evidence of this potential confound (age-adjusted t-score ~ age: $R^2 = 0.003$, $F(1, 148) = 0.484$, $p = .488$). Participants also underwent a brief prestudy audio test to ensure that they could play the verbal instructions from their computers (Nussenbaum et al., 2020).

Task-Switching Paradigm

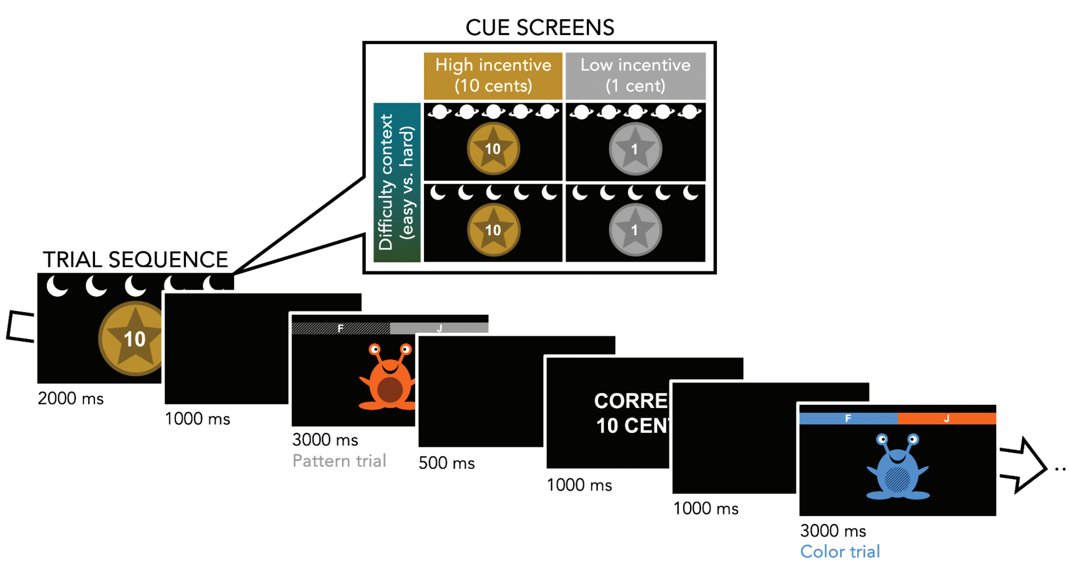
Structure of Task-Switching Trials

The online study was a child-friendly task-switching paradigm (Figure 1) with cartoon alien stimuli. There were two colors of aliens (blue, orange) with two types of stomachs (striped, solid), for a total of four unique aliens (equalized for luminance). In some trials, participants reported the alien's body color; in other trials, participants reported the alien's stomach pattern. Whether participants should respond to an alien's body color or stomach pattern was depicted with a probe above the stimulus that meaningfully related to the target action (blue/orange bar signaled a color trial; striped/solid bar signaled a pattern trial; Chevalier & Blaye, 2009). Switching between color and pattern trials engenders cognitive control demands, so infrequent task switches across a series of trials should be experienced as easier while frequent task switches across a series of trials should be experienced as harder. Accordingly, during the easy conditions, participants experienced low task switch probabilities, whereby 20% of trials switched from the previous trial type. Meanwhile, during the hard conditions, participants experienced high task switch probabilities, whereby 50% of trials switched from the previous trial type.

Participants were told that correct and rapid task-switching performance would be rewarded with a monetary bonus. Participants earned 1 or 10 cents per trial for accurate responses, and they received an additional $1 bonus if their average response time throughout the task was less than 2,000 ms or an additional $2 bonus if their average response time was less than 1,000 ms. Incentivizing correct and rapid performance was based on previous literature (Bowers et al., 2021; Padmala & Pessoa, 2011) and allowed for both accuracy and speed to be examined as outcome measures of motivated cognitive control. The 240 trials each included a blank screen (1,000 ms), a color or

Figure 1

Schematic Representation of Learning Task



Note. (Cue screens) Before completing a series of trials, participants viewed a cue screen showing which mini reward block they were in. There were four types of mini reward blocks: easy 10 cents, easy 1 cent, hard 10 cents, and hard 1 cent. The incentive cue (1 or 10 cents) was explicitly displayed with gold and silver coins, respectively. The difficulty cue (planet or moon galaxy) needed to be learned through experience. Participants could use these cues to guide their cognitive effort during the upcoming set of task-switching trials. (Trial sequence) During each trial, participants viewed a cue screen, alien stimulus target, then performance-based feedback with their earned incentive. The following trial either implemented the same trial type or switched to a different trial type (in the example pictured, the trial switched from pattern to color). The presence of a blue/orange bar above the alien stimulus signaled a color trial, while the presence of a striped/solid bar above the stimulus signaled a pattern trial. Participants responded using the F and J keys; these labels were included on the bars to remind participants to press those keys for each color or pattern.

pattern probe with an alien stimulus (3,000 ms response window), another blank screen (500 ms), and a feedback screen (correct, incorrect, or too slow) that revealed the amount earned (1,000 ms; Figure 1, trial sequence).

Primary Manipulation of Reward and Difficulty Information

Critically, to shape the value of cognitive control according to multiple sources of information, these trials were embedded within a 2×2 block design, inspired by Otto and colleagues (Otto & Vassena, 2021; Otto et al., 2022). First, the 240 trials were divided into six, 40-trial blocks with two levels of difficulty. As mentioned above, the easy blocks had a low, 20% task switch probability while the hard blocks had a high, 50% task switch probability. Since prior studies indicate that a task switch rate of 50% is experienced as more demanding (Devine & Otto, 2022; Mittelstädt et al., 2018) than a lower task switch rate (e.g., 20%), the difficulty manipulation should imbue greater cognitive control costs in the hard than easy condition.

Within each block of 40 trials at high or low difficulty, there were two, 20-trial mini reward blocks. Mini reward blocks were defined by the incentives at stake, 1 or 10 cents, for accurate and rapid performance. Thus, the reward manipulation should imbue greater cognitive control benefits for the 10 than 1 cent condition. The mini reward blocks, and the difficulty context blocks they were situated in, were presented to participants in a pseudorandomized order, balanced across age and gender. Participants were offered 1 min breaks after completing 80 and 160 trials.

Each 20-trial mini reward block was preceded by a cue screen (2,000 ms; Figure 1, cue screens) displaying information about the reward and difficulty levels of the upcoming trials. For all participants, seeing a silver coin signaled 1 cent incentives in the forthcoming block and seeing a gold coin signaled 10 cent incentives in the forthcoming block. Planets or moons along the top of the screen represented the difficulty level, with one cue signaling a forthcoming easy block and the other cue signaling a forthcoming hard block. The assignment of planets and moons to difficulty levels was random for each participant. Since these difficulty cues were not instructed in advance, participants had to acquire the cue associations during the task. Through experience with the task switch rates, participants could learn which difficulty levels the planets and moons corresponded to.

Together, participants could use the information on the cue screens—about how demanding the upcoming trials would be and how much they would earn for performing well in them—to adjust their cognitive effort in task-switching according to learnable difficulty and instructed reward. Crucially, previous research in similar age ranges has established that the participants tested here could plausibly detect, and voluntarily leverage, the incentive and demand dimensions of the cue screens to guide their cognitive effort allocation proactively (Chevalier & Blaye, 2016; Jin et al., 2020; Niebaum & Munakata, 2020; Veselic et al., 2021).

Dependent Variables Measuring Cognitive Effort

We computed participants' accuracy and reaction time for each mini reward block. The task manipulations abided by a fully within-subjects design, so we could examine, for each participant, these performance measures in one mini reward block *relative* to the other mini reward blocks. Given that we motivated correct and rapid responses with a monetary bonus, we treated greater accuracy and faster reaction time as indices of successful cognitive effort investment in a mini reward block. Both types of performance measures can be informative for evaluating the degree of reward- and difficulty-modulated cognitive effort. However, we aimed to characterize how the value of cognitive effort is *learned*, and studies of reinforcement learning through adolescence often use the accuracy of trial-wise responses to assess how reward shapes choice behavior across age and time (Nussenbaum & Hartley, 2019). Therefore, accuracy is regarded as the key dependent variable of interest in this developmental study to make our findings readily comparable with relevant prior literature.

Practice Phase

To ensure that child, adolescent, and adult participants were exposed to the structure and demands of task-switching before they were presented with additional reward and difficulty information, the sample underwent a 120-trial practice phase prior to completing the learning task. Participants had the opportunity to engage in an analogous task-switching paradigm but without cue screens or incentives. All participants finished, in order, a 30-trial easy block, 30-trial hard block, 30-trial easy block, and 30-trial hard block. As supported by exploratory data visualizations, the practice phase was effective in familiarizing participants with the paradigm's instructions and response procedure (Supplemental Figure S3).

Secondary Manipulation of Learnable and Instructed Information

In the experiment described above, reward information was instructed on the cue screens while difficulty information was learnable (Figure 1, cue screens). To clarify the role of learnable versus instructed difficulty information in cognitive effort value learning, we ran another experiment in 152 participants ages 10–20 years. After excluding two participants for failing to respond to more than 90% of practice trials (ages = 17.08 years, 19.82 years), a final sample of 150 participants was included in the secondary data analyses. Importantly, the samples of both experiments were matched along key demographic variables (Supplemental Table S1). All procedures of the secondary experiment were the same as those in the first, except difficulty information was explicitly labeled on the cue screens (Supplemental Figure S4).

Post-Task Ratings

After the practice phase and learning task, participants completed two sets of post-task ratings about each reward-difficulty cue (Figure 1, cue screens) according to 7-point Likert scales. First, participants were asked to report how hard they tried in each planet or moon galaxy (from "Tried Very Little" to "Tried Very Hard"); this allowed for a comparison between the degree to which participants' self-reported cognitive effort aligned with their task-switching performance (quantified by their accuracy). Second, participants were asked to report how hard they found each galaxy (from "Very Easy" to "Very Hard"); this checked whether the participants were aware of the different demands in the easy and hard difficulty contexts.

Additionally, a subjective value of money scale was administered, in which participants were asked to rate how much the amounts of money used in the task meant to them. These ratings were indicated with a sliding bar (from "Not much money" to "A lot of money"), which were converted to a value representing the percent change from 1 to 10 cents. If the titration of cognitive effort according to reward and difficulty information increases from childhood to adulthood, then it should be confirmed that our result is not a consequence of a simple confound—that 1 and 10 cents were valued differentially across age. Prior work has demonstrated age-consistent valuation of monetary outcomes (Insel et al., 2017, 2019; Insel & Somerville, 2018; Rodman et al., 2021), but this consistency was nonetheless verified within the sample collected here, percent change from 1 to 10 cents ~ age: $R^2 = 0.003$, $F(1, 136) = 0.388$, $p = .535$.

Following these post-task ratings, participants were directed to self-report questionnaires. These questionnaires indexed individual variability in motivational processes thought to be relevant for using reward and difficulty information to shape cognitive effort (Supplemental Methods).

Analytical Approach

Primary Mixed-Effects Modeling Overview

Mixed-effects models from the *lmerTest* package (a wrapper for the *lme4* package, plus additional inferential output; Version 3.1.3; Bates et al., 2015; Kuznetsova et al., 2017) in R (Version 4.1.2; R Core Team, 2021) were used to test our first three hypotheses, that learning the value of cognitive effort undergoes refinement from childhood to adulthood. Two models were run with identical predictors (enumerated below) but different dependent variables: sum of binary response *accuracy* across a mini reward block and mean of continuous response *reaction time* (measured in ms) across a mini reward block. Since the dependent variable for the *accuracy* model was the number of correct trials in a mini reward block out of the total number of trials in that block, the *accuracy* model was fit as binomial generalized linear mixed-effects analysis with the glmer function. The distributional assumption of the binomial model was appraised with a posterior predictive check (using the posterior_predictive_check function from the *performance* package in R; Version 0.9.1; Lüdecke et al., 2021) and deemed fulfilled. The *reaction time* model was fit as linear mixed-effects analysis with the lmer function. The distributional assumption of the Gaussian model was appraised with a qq-plot and posterior predictive check (using the posterior_predictive_check function from the *performance* package in R; Version 0.9.1; Lüdecke et al., 2021). These tests confirmed that *reaction time* was reasonably normal.

Post hoc tests were conducted for key results to better understand age-related changes in the influence of the reward-difficulty manipulation on cognitive effort exertion. These tests were run using the emmeans function from the *emmeans* package in R (Version 1.7.5; Lenth, 2022). For each test, estimated marginal mean differences between conditions of interest were compared for instructive age values extracted from a fitted model: two values near the youngest end of our age range (10.50, 11.50 years), two values near the oldest end of our age range (19.50, 20.50 years), and two values in the middle of our age range (15, 16 years). p values were corrected for multiple comparisons according to the Holm method.

Primary Predictor Variables

The fixed main effect predictors were *age* (in years; calculated continuously and treated as a metric variable), *time* (treated as a categorical ordinal variable with three levels; early: trials one-80, middle: trials 81–160, late: trials 161–240), *difficulty* (treated as a categorical variable with two levels; easy and hard), and *incentive* (treated as a categorical variable with two levels; low and high). Each of these fixed main effect predictors was permitted to interact with each other. *Participant ID* was associated with a random intercept to account for repeated measurements. To mind the possibility that there may have been between-participant variance in the shape of the effect of *time*, *difficulty*, or *incentive* on accuracy and reaction time, the necessity of associating *time*, *difficulty*, and *incentive* with random slopes was considered but deemed superfluous (Supplemental Methods).

Assessing the Significance of Primary Effects

Analyses of deviance (type II, Wald χ^2 tests with Satterthwaite approximations for degrees of freedom) using the ANOVA function from the *car* package in R (Version 3.1.0; Fox & Weisberg, 2019) were performed on the mixed-effects models described above. All main effects and interactions produced by the models demonstrating $p < .05$ were interpreted as statistically significant, while all main effects and interactions produced by the models demonstrating $p < .10$ were interpreted as marginally significant. These main effects and interactions were examined visually using the plot_model function from the *sjPlot* package in R (Version 2.8.10; Lüdecke, 2021), as well as the ggpredict function from the *ggeffects* package in R (Version 1.1.2; Lüdecke, 2018) in concert with variants of the ggplot function from the *ggplot2* package in R (Version 3.4.1; Wickham, 2016). Raw data visualizations were implemented using variants of the ggplot function from the *ggplot2* package in R (Version 3.4.1; Wickham, 2016).

Evaluating Secondary Manipulation of Information

To test our fourth hypothesis, that there are even greater age differences in behavior—reflecting increasingly efficient valuations of cognitive effort into adulthood—when reward and difficulty information are both instructed, an *accuracy* mixed-effects model identical in structure and distributional assumptions to that described for the primary experiment was fit to participants' responses in the secondary experiment. The significant main effects and interactions were assessed using the same tools as described before.

Additional Analyses

To build upon our primary analyses, and to test our fifth hypothesis, we also ran a mixed-effects model that captured age-related changes in metacognitive awareness of cognitive effort exertion for each condition. The dependent variable was participants' 7-point Likert *effort rating* in response to the question: "How hard did you try in this galaxy?" As before, the model was fit as linear mixed-effects analysis with the lmer function, then the distributional assumption of the model—that *effort rating* was reasonably normal—was appraised and confirmed.

The fixed main effect predictors were *age*, *accuracy* for each galaxy, and *galaxy*, where *galaxy* corresponded to the four types of mini reward blocks: easy 10 cents, easy 1 cent, hard 10 cents, and hard 1 cent. The significant main effects and interactions were assessed using the same tools described earlier. In this analysis, we chose to model *galaxy* as four levels of one variable, rather than two levels of *difficulty* and two levels of *incentive* (as in the primary analyses). This decision was made because both *age* and *accuracy* were continuous metric predictors here, so treating *galaxy* as a single variable facilitated ease of model interpretation. Moreover, modeling *galaxy* as a single variable was more closely tied to the data collected: participants were asked to rate their effort *at the level of the condition overall*, rather than at the level of *difficulty* (e.g., "How hard did you try for planets?") or *incentive* (e.g., "How hard did you try for gold coins?") alone.

Transparency and Openness

The preregistration for the primary experiment, submitted before data collection, can be found at https://osf.io/h9cxv. The preregistration for the secondary experiment, submitted before data analysis, can be found at https://osf.io/3epua. Minimal updates to these preregistrations were made during data analysis (Supplemental Methods). All anonymized data and code to produce the figures and perform the analyses are available at https://github.com/andlab-harvard/cogeff_paper_phaneuf-hadd.

Results

Paradigm Validation and Data Distribution Checks

Paired, one-tailed *t* tests were conducted to verify that participants' performance was modulated by the learnable difficulty manipulation. As expected, participants demonstrated more correct and faster responses for the easy relative to hard difficulty context (accuracy: $t(149) = 3.228$, $p < .001$; reaction time: $t(149) = -7.683$, $p < .001$).

It was important that there were comparable opportunities for participants to modulate their behavior under each combination of our reward and demand manipulations. A lack of modulation opportunity for any condition relative to the others would be revealed by a uniquely small degree of *accuracy* or *reaction time* variability. If a condition produced such variance compression, then we would be concerned about our ability to detect age-related changes in that condition over time. To this end, we visualized performance distributions across each mini reward block (Supplemental Figure S5). Crucially, we did not find evidence of unbalanced variance compression for *accuracy* or *reaction time* for any incentive amount or difficulty context.

Reward and Difficulty Guided Cognitive Effort Differently Across Time and Age

To investigate how cognitive effort exertion is tuned across time and age according to instructed reward and learnable difficulty information, we first characterized the interacting influences of *age*, *time*, *difficulty*, and *incentive* on the *accuracy* of responses during the learning task. From the *accuracy* mixed-effects model (Supplemental Table S2), we found significant main effects of *age*, $\chi^2(1, N = 150) = 10.42$, $p < .01$, and *difficulty*, $\chi^2(1, N = 150) = 9.14$, $p < .01$, such that *accuracy* increased with age and was greater for the easy relative to hard difficulty context.

Building from these main effects, and in support of our first hypothesis, we found a significant two-way interaction between *age* and *incentive*, $\chi^2(1, N = 150) = 8.41$, $p < .01$; *accuracy* improved more steeply for higher than lower incentives with increasing age. Post hoc tests of estimated marginal mean differences between reward amounts were conducted at instructive age values (Supplemental Figure S6) and confirmed that, consequently, younger participants trended toward elevated accuracy for lower than higher incentives (10.50 years: $p_{\text{corrected}} < .10$, 11.50 years: $p_{\text{corrected}} < .10$) and older participants were more accurate for higher than lower incentives (19.50 years: $p_{\text{corrected}} < .10$, 20.50 years: $p_{\text{corrected}} < .05$). Meanwhile, adolescents did not demonstrate incentive-based differences in the accuracy of their responses (15 years: $p_{\text{corrected}} = .888$, 16 years: $p_{\text{corrected}} = .603$). This two-way interaction was qualified by a significant three-way interaction between *age*, *time*, and *incentive*, $\chi^2(2, N = 150) = 9.18$, $p < .05$; Figure 2A. The three-way interaction contrasts with prior work, as the reward-based titration of *accuracy* in adulthood (observed in the preceding two-way interaction) was evident during the beginning and middle of learning, but not the end (see intersecting incentive lines across age in the early and middle panels, but overlapping incentive lines across age in the late panel, of Figure 2A). This result opposes our third hypothesis, which predicted that the interacting influence of *age* and *incentive* on cognitive effort would emerge, rather than dissipate, over *time*.

On the other hand, and in support of our second hypothesis, we found a marginally significant two-way interaction between *age* and *difficulty*, $\chi^2(1, N = 150) = 3.01$, $p < .10$; Figure 2B; *accuracy* improved slightly for the easy difficulty context with increasing age but remained stable for the hard difficulty context. Again, we did not find evidence for our third hypothesis, which predicted that the interacting influence of *age* and *difficulty* on cognitive effort would emerge over *time*, or that there would be interactions between *incentive* and *difficulty*. There were no other significant main effects or interactions than those listed here (*p*s > .181). Together, these results indicate that reward and difficulty information guided how much cognitive effort was allocated to facilitate accuracy in separable ways across time and age: higher incentives promoted markedly more correct responses, especially into adulthood earlier in the task, while fewer demands promoted slightly more correct responses, especially into adulthood throughout the task.

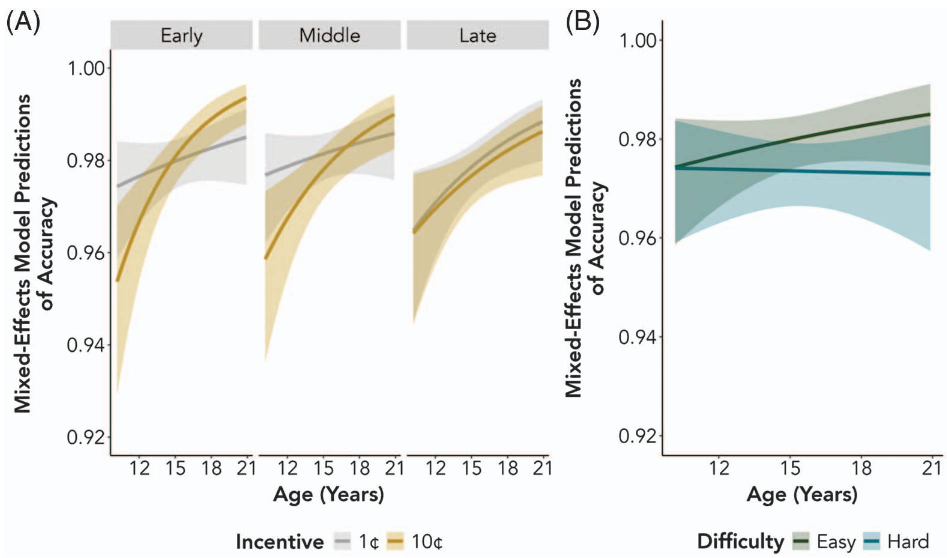
We also observed statistically significant main effects and marginally significant interactions in the mixed-effects model treating *reaction time* as the dependent variable (Supplemental Results). Importantly, however, we verified the absence of speed–accuracy trade-offs across these two models by conducting a sensitivity analysis, in which the *reaction time* mixed-effects model was run on correct trials only (Supplemental Table S3).

Robustness of Age-Related Change

To ensure that the reported effects of *age* on *accuracy* were more likely to be driven by age-related changes in cognitive and motivational processes, rather than individual differences in constructs that could influence how cognitive effort is adjusted to reward and difficulty information across time, we considered the potential roles of three additional variables. While doing so, we treated age as a

Figure 2

Accuracy Was Moderated by the Incentives Offered for Correct Responses Across Age and Time, While Accuracy Was Marginally Moderated by the Difficulty of the Task-Switching Context Across Age



Note. (A) Conditioned on the other main effects and interactions in the mixed-effects model, accuracy increased more rapidly for higher than lower incentives with age. As a result of the differential steepness of these slopes, younger participants were somewhat more accurate for lower than higher amounts, adolescents' accuracy was similar across amounts, and older participants were more accurate for higher than lower amounts. These patterns were especially true earlier in the learning task. (B) Conditioned on the other main effects and interactions in the mixed-effects model, accuracy increased slightly more rapidly for the easy than hard difficulty context with age. The differential steepness of these slopes point to the emergence of marginally greater accuracy for less demanding blocks into adulthood. Shading represents 95% confidence intervals around fitted lines.

control covariate, rather than as an interacting predictor. First, we evaluated the role of participants' baseline task-switching ability, as a proxy for cognitive control capacity when reward and difficulty cues are absent. Baseline ability was operationalized as mean accuracy for the last block of each difficulty context in the practice phase. Second, we evaluated the role of participants' intrinsic motivation to engage in cognitively demanding tasks, measured using age-appropriate versions of the Need for Cognition scale (Cacioppo et al., 2013; Keller et al., 2019). Third, we evaluated the role of participants' motivation to pursue reward, measured using age-appropriate versions of the Behavioral Activation System Drive subscale (Carver & White, 1994; Muris et al., 2005). For full details of our approach, see Supplemental Methods. Through these follow-up analyses, we determined that although these constructs explained some additional variance in learning the value of cognitive effort, age continued to be a significant predictor of *accuracy*, even when it was treated as a covariate (Supplemental Table S4). This collection of findings confirms that age-related changes in the use of reward and difficulty information are more central than these constructs are to understanding when cognitive effort is deployed and withheld.

Fully Instructed Information Alters Overall Task Demands

To clarify how cognitive effort exertion is regulated when reward and difficulty information are both instructed, we examined the interacting influences of *age*, *time*, *difficulty*, and *incentive* on the *accuracy* of responses during the learning task. From the secondary experiment's accuracy mixed-effects model (Supplemental Table S5), we found significant main effects of *age*, $\chi^2(1, N = 150) = 9.08$, $p < .01$, and *difficulty*, $\chi^2(1, N = 150) = 5.55$, $p < .05$. As in the primary experiment, *accuracy* increased with age and was greater for the easy relative to hard difficulty context. Failing to support our fourth hypothesis, we did not find any other significant main effects or interactions ($ps > .100$). These results suggest that explicitly cueing difficulty information does not simply amplify the effects observed in the primary experiment. Rather, offering participants fully instructed information removes the demands imposed by learning, which may alter how challenging the task environment is overall, with unique consequences for age-related behavior. An exploratory one-tailed t test comparing accuracy between the primary and secondary experiments found that participants were marginally more correct in the secondary experiment, $t(294.81) = -1.384$, $p = .084$.

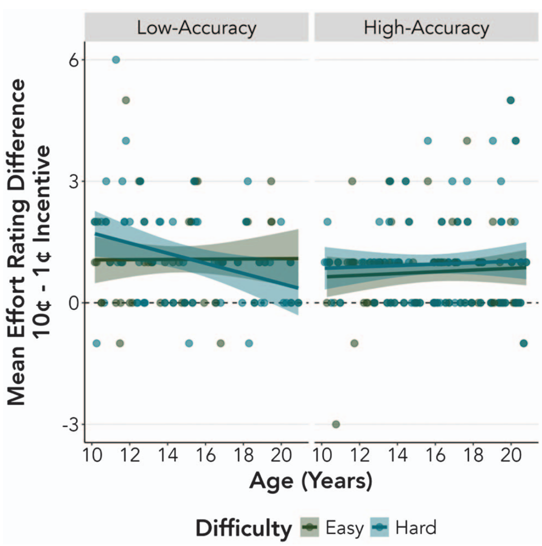
Metacognitive Awareness of Cognitive Effort Across Age

We reported above that reward and difficulty guided behavioral signatures of cognitive effort in age-varying ways. To probe whether participants throughout the sample had metacognitive awareness of the differential effort they spent in each condition, we considered how responses to, "How hard did you try in this galaxy?" tracked actual performance during the learning task from the primary experiment across age. From our *effort rating* mixed-effects model, we found a significant main effect of *galaxy*, $\chi^2(3, N = 149) = 249.17$, $p < .001$, such that participants of all ages reported expending greater effort for the galaxies associated with higher than lower incentives in both difficulty contexts. Surprisingly, an identical main effect—that perceptions of demand were elevated for higher incentives rather than harder difficulty contexts—was found in response to, "How hard was this galaxy?" (Supplemental Results). The main effect from the *effort rating* mixed-effects model was qualified by a significant three-way interaction between *age*, *accuracy*, and *galaxy*, $\chi^2(3, N = 149) = 8.07$, $p < .05$; Figure 3. Across age, the highest performing participants, the relatively "best task-switchers," reported greater *effort ratings* for the 10 than 1 cent conditions in the easy and hard difficulty contexts alike (Figure 3, right panel). However, and as predicted by our fifth hypothesis, *effort ratings* varied with age, incentives, and difficulty for the lowest performing participants, the relatively "worst task-switchers" (Figure 3, left panel). Namely, low-accuracy younger participants reported greater *effort ratings* for the 10 than 1 cent conditions, especially in the hard difficulty contexts. When the task was more demanding, these participants said that they tried the most for the larger rewards. Meanwhile, low-accuracy older participants reported greater *effort ratings* for the 10 than 1 cent conditions, especially in the easy difficulty contexts. When the task was less demanding, and unlike the low-accuracy younger participants, these low-accuracy older participants said that they tried the most for the larger rewards. Finally, low-accuracy adolescents reported greater *effort ratings* for the 10 than 1 cent conditions in both difficulty contexts. In other words, low-accuracy adolescent participants mirrored the self-reported cognitive effort patterns of the high-accuracy participants. There were no other significant main effects or interactions than those listed here (*p*s > .170).

In sum, the greatest differences in *effort ratings* between incentive amounts were for the low-accuracy younger participants in the hard galaxies and for the low-accuracy older participants in the easy galaxies. Even though the younger participants exhibited more correct responses for lower than higher incentives in our primary experiment's *accuracy* mixed-effects model from earlier, they endorsed the opposite in the post-task ratings, particularly in the hard difficulty context for worse performers. Older participants, on the other hand, exhibited more correct responses for higher than lower incentives in the *accuracy* mixed-effects model, which they appropriately endorsed here, particularly in the easy difficulty context for worse performers. Adolescents responded similarly for higher and lower incentives in the *accuracy* mixed-effects model but endorsed trying harder for the higher than lower incentive galaxies across difficulty levels; their self-reported cognitive effort did not translate to their realized performance in the learning task.

Figure 3

Metacognitive Awareness of Cognitive Effort Increases With Age for Relatively Low-Performing Participants



Note. The figure is faceted by (left panel) participants averaging below-mean ("low-accuracy") responses for each difficulty level and (right panel) participants averaging above-mean ("high-accuracy") responses for each difficulty level. A difference greater than 0 along the *y*-axis means that participants reported greater *effort ratings* for the 10 than 1 cent conditions, a difference less than 0 means that participants reported greater *effort ratings* for the 1 than 10 cent conditions, and a difference of 0 means that participants reported equivalent *effort ratings* for the 10 and 1 cent conditions. The concentration of data above the dashed line at $y = 0$ demonstrates that participants of all ages and performance levels endorsed trying harder for higher incentives. (Right panel) The parallel and overlapping difficulty context lines for the high-accuracy participants indicate that their greater *effort ratings* for the 10 than 1 cent conditions did not change with age or demand. (Left panel) Contrastingly, the intersecting difficulty context lines for the low-accuracy participants indicate that their greater *effort ratings* for the 10 than 1 cent conditions change with age and demand, such that younger participants endorsed titrating their cognitive effort according to reward most in the hard difficulty context while older participants endorsed titrating their cognitive effort according to reward most in the easy difficulty context. Adolescents endorsed titrating their cognitive effort according to reward similarly across difficulty contexts. Shading represents 95% confidence intervals around fitted lines.

Discussion

The present study examined the ways in which multiple value signals are detected, integrated, and leveraged to support efficient cognitive effort exertion in older children through young adults. This was accomplished by manipulating reward and difficulty information across two experiments: a primary one in which the reward cue was instructed but the difficulty cue was learnable, and a secondary one in which both cues were instructed. In the primary experiment, we found that reward and difficulty information directed the deployment of cognitive effort: while less demanding contexts promoted greater accuracy at the group level, the titration of effort according to easy and hard difficulty tended to emerge into adulthood. Similarly, the titration of cognitive effort according to higher and lower incentives changed with age. Older participants—especially early in the task—were economically more accurate for larger earnings, while adolescents were comparably accurate for smaller and larger earnings alike. Interestingly, these results were specific to this somewhat more challenging environment, in which participants were taxed with learning about the difficulty cue. When we removed learning demands, and effectively made every condition in the study easier in a secondary experiment, there was no evidence that value cues guided behavior increasingly into adulthood.

Even though we found age differences in value-guided performance during the task in the primary experiment, participants of all ages self-reported that they exerted more effort for greater rewards. Unexpectedly, younger participants performed marginally better for smaller earnings, despite their self-reports of devoting more effort to larger earnings. These results are consistent with prior work demonstrating that adolescents' goal-directed behavior is motivated equivalently by different reward amounts (Insel et al., 2017; Rodman et al., 2021). These results also align with earlier demonstrations that adults' cognitive effort decisions are guided by both reward and difficulty information (Bijleveld et al., 2009; Otto et al., 2022) and that adults endorse higher demands for greater incentives (Fairclough & Ewing, 2017). Taken together, this pattern of findings suggests that *which types* of information are heeded, and *how many* sources of information are heeded, drive maturing estimations of the value of cognitive effort from late childhood to early adulthood.

A growing body of research reveals that goal-directed behavior comes to be shaped by varying incentives during the transition from adolescence into adulthood: while adolescents tend to pursue reward-associated goals regardless of the magnitude of the reward, adults' behavior is modulated by the degree of previous or current rewards at stake (Cohen et al., 2022; Insel et al., 2017; Rodman et al., 2021; Störmer et al., 2014). In the primary experiment, this meant that older participants adaptively upregulated their cognitive effort when it was most worthwhile—when the benefits of their effort were greatest, following the higher incentive cue screens. This was especially true during early and middle learning. This time-dependent result stands in slight contrast to Otto et al. (2022) but could be because, by the end of learning, extensive task-switching experience had accumulated, and cognitive effort could be allocated sufficiently for both degrees of reward. Alternatively, this time-dependent result could be because adults have been shown to rely more on instructed information—like the reward cue—at the beginning of learning before experiential knowledge takes over (Decker et al., 2015). In contrast, adolescents tend to make decisions based on their own, personal exposure to rewarding outcomes (Decker et al., 2015). Unlike the older participants, adolescents were not economical about their cognitive effort exertion, regardless of how challenging the environment was. They invested similar effort into higher and lower incentive galaxies. Younger participants were even less effective at titrating their cognitive effort, performing with greater precision for the lower than higher incentive galaxies in the somewhat more demanding primary experiment.

All participants, though, self-reported trying their hardest in the higher incentive galaxies. This was especially true of low-performing children and adults in the hard and easy difficulty contexts, respectively. This result is interesting for two reasons. First, it concurs with Otto et al. (2022), which suggested that low-performing adults aimed to be maximally efficient with their cognitive effort. Like Jane from the Introduction section, these adults integrated across reward and difficulty information to selectively engage their effort when the highest rewards were at stake in the easiest conditions. We found that the low-performing children did not have this aim in mind. Rather, they intended to employ their cognitive effort when the highest rewards were at stake in the hardest conditions—contexts in which their effort was least worthwhile. Second, this self-report result, combined with the behavioral data described earlier, suggests that metacognitive awareness tracked performance more faithfully with increasing age. Because the older participants endorsed trying most in the higher incentive galaxies, and they actually performed better in those galaxies during the task in the primary experiment, they had the greatest metacognitive awareness of their goal: to engage cognitive control for the larger rewards, then translate this goal successfully to action. On the other hand, adolescents and younger participants failed to translate their goals into actions. Aligning with previous research, adolescents reported wanting the larger rewards (Bowers et al., 2021; Fryer, 2011) but did not take the extra step of tuning their cognitive effort to match their aims (Davidow et al., 2018). Novelly, since younger participants also reported wanting the larger rewards but performed better for the opposite, we speculate that they may have "choked under pressure" while pursuing their aims (Baumeister, 1984; DeCaro et al., 2011; Mobbs et al., 2009; Sattizahn et al., 2016). For younger participants, having larger rewards at stake could imbue a high-pressure environment that interferes with accurate responding. By intending to excel for the larger rewards, younger participants may have disposed themselves to compromise their task-switching performance.

Consistent with prior work, in the primary experiment, we also found that cognitive effort was increasingly shaped by cueing varying difficulty levels from childhood to adulthood (Chevalier et al., 2015; Ganesan & Steinbeis, 2021; Martinez et al., 2018; Niebaum et al., 2019, 2021). Similar to our reward result, older participants' behavior was most modulated by the difficulty manipulation, with slightly greater accuracy elicited by the most worthwhile, easier contexts. This could be due to the nature of difficulty information: when the environment is challenging enough for difficulty information to have some utility, adults may value knowing how demanding something is, and use this insight to guide their behavior, to a greater extent than children and adolescents. This could also be due to the nature of learnable information: having to associate the planet and moon galaxies with difficulty levels through repeated experiences could have been a hindrance to younger participants and adolescents adjusting their behavior according to demand cues as much as their older participant counterparts. Regardless of whether older participants' behavior was moderated by *difficulty* or by *learnability*, adults may have been the most apt to leverage an additional source of information in the primary experiment, layered on top of the incentive cues, because a sophisticated set of decision-making strategies becomes increasingly available with age (Jacobs & Klaczynski, 2002). In the face of simultaneous information streams, perhaps children leaned on the more salient, instructed rewards to direct their behavior.

Interestingly, in the secondary experiment's somewhat less challenging environment, participants of all ages performed better in the easy than hard difficulty contexts. Given the lack of significant multiway interactions between age and reward or difficulty, there was no evidence that older participants uniquely adjusted their cognitive effort according to incentive or demand information in an economical manner, as they had in the primary experiment. That is, in the secondary experiment, younger participants were just as apt to titrate their cognitive effort according to the difficulty cues in an adult-like way, which was perhaps inaccessible to them in the primary experiment. Together, the pair of studies enrich our understanding of age-related changes in cognitive effort value learning by implicating the role of the environment: what sources of information matter for guiding behavior depends on how well one can perform in that domain.

Importantly, we substantiated the robustness of these patterns of age-related changes by investigating several other candidate mechanisms for inducing individual variability in cognitive effort value learning. Namely, we evaluated how baseline task-switching ability, intrinsic motivation to engage in cognitively demanding tasks, and motivation to pursue reward influenced accuracy. These supplemental analyses revealed that age was a reliably significant predictor of performance. Moreover, through further supplemental analyses, we showed that our findings could not be explained by simple speed–accuracy trade-offs: the rapidity of responses was not dependent upon their correctness.

Constraints on Generality

Our population consisted of children, adolescents, and adults from the United States who had access to a laptop or desktop computer with a reliable internet connection. These participants were also screened for a number of exclusion criteria relevant to their ability to complete an asynchronous, online study. While we took care to recruit participants across an even age and gender distribution (Supplemental Figure S1), we did oversample participants who identified as White/Caucasian. Therefore, our results may not generalize to populations with relatively reduced technological access or those with other racial and ethnic identities. Additionally, these participants were screened for a number of exclusion criteria thought to influence reward learning, as updating the value of cognitive effort according to incentive information was a core component of this study. Future research should examine how individuals with varying neurodivergent identities exert their cognitive effort in response to instructed reward and learnable difficulty cues.

Moreover, our population was cross-sectional; we sampled participants from 10 to 20 years, rather than measuring individual participants at several time points as they aged. Consequently, the age-related changes in learning the value of cognitive effort that we report here at the group level may not track at the individual level. The developmental trajectories of detecting, integrating, and leveraging reward and difficulty information could vary for single participants, and further work should address this gap.

We also included 1 and 10 cent incentives as our reward manipulation. Our finding, that reward-based titration of cognitive effort emerged into adulthood, may not hold for other *degrees* of incentives, or for the *presence* of incentives. In fact, the mere availability of reward likely shapes behavior the most during adolescence (Ernst et al., 2006; Geier & Luna, 2009; Geier et al., 2010; Strang & Pollak, 2014; but see Magis-Weinberg et al., 2019). Nonetheless, we note that the relative difference in rewards—more than absolute magnitude—has been shown to be the critical moderator of goal-directed behavior across age (Elliott et al., 2008; Insel & Somerville, 2018; Otto & Vassena, 2021; Seymour & McClure, 2008).

Similarly, we included 20% and 50% task switch probabilities as our difficulty manipulation, and our findings may shift for tasks with different degrees of overall challenge. Indeed, when we fully instructed reward and difficulty with explicit cues in our secondary experiment, the entire task became less somewhat demanding, which minimized how much these information sources guided cognitive effort. Therefore, it is possible that, in relatively more challenging contexts, individuals of all ages would call upon difficulty information to a greater extent to shepherd choices about their cognitive effort expenditure. We look forward to follow-up studies with other cognitive control paradigms that impose greater demands across conditions.

Finally, we recognize that our measures of performance, greater accuracy and faster reaction time, are not indicative of cognitive effort investment in all scenarios. Performance-based measures of cognitive effort can also be affected by internal affordances like executive functioning capacity (Kramer et al., 2021). Our sample was evenly distributed from childhood to adulthood because the present study was designed to identify the effects of incentive and demand information on cognitive effort allocation across age and time. A study design with a different sampling strategy (e.g., dense sampling from a narrower age range but wider executive functioning capacity range) would be more appropriate for isolating complex interactions between task performance and individual differences in executive functioning capacity. Future work should adopt these alternative sampling strategies to characterize how executive functioning capacity, and other important individual differences, influences age-related changes in economical cognitive effort investment.

Conclusions

In sum, this study furthers our understanding of age-related variability in the use of cost–benefit analyses to guide cognitive effort allocation over time. Indeed, we discovered that how cognitive effort is valued from late childhood to early adulthood depends differentially on instructed reward and learnable difficulty information. While older participants, especially early in learning, leverage both types of information to mobilize their cognitive effort in an economical manner, younger participants and adolescents claim to modulate their behavior according to incentive opportunities, but they do not actually translate their aims into action. This cumulative finding supports prior work indicating that reward moderates cognitive effort with increasing age (Insel et al., 2017; Smith et al., 2011). It also indicates that additional information types—above and beyond proximal rewards—can be exploited into adulthood as more sophisticated decision strategies come online and are arbitrated between (Decker et al., 2015; Smid et al., 2023).

Discovering that the value of cognitive effort changes with age has important consequences for applied education research. Since the reward-difficulty cues do not affect behavior uniformly from childhood to adulthood, or in environments that vary in their overall challenge, future work should consider how students of different ages weigh unique sources of information when deciding how much to try, for instance, on an assignment. If adolescents' cognitive effort exertion is consistently incentive-insensitive, signaling that an assignment is paramount for a high schooler by associating it with a bigger impact on their letter grade may be ineffectual for promoting their prioritization of that assignment. Of benefit to this real-world implication and others, characterizing age-related refinements in learning to titrate cognitive effort in accordance with multiple cues about its worthwhileness is a crucial step forward.

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