



# Seizing the opportunity: Lifespan differences in the effects of the opportunity cost of time on cognitive control

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## ARTICLE INFO

### Keywords:

Lifespan development  
Opportunity costs  
Cognitive control  
Cognitive effort

## ABSTRACT

Previous work suggests that lifespan developmental differences in cognitive control reflect maturational and aging-related changes in prefrontal cortex functioning. However, complementary explanations exist: It could be that children and older adults differ from younger adults in how they balance the effort of engaging in control against its potential benefits. Here we test whether the degree of cognitive effort expenditure depends on the opportunity cost of time (average reward rate per unit time): if the average reward rate is high, participants should withhold cognitive effort whereas if it is low, they should invest more. In Experiment 1, we examine this hypothesis in children, adolescents, younger, and older adults, by applying a reward rate manipulation in two cognitive control tasks: a modified Erikson Flanker and a task-switching paradigm. We found that young adults and adolescents reflexively withheld effort when the opportunity cost of time was high, whereas older adults and, to a lesser degree children, invested *more* resources to accumulate reward as quickly as possible. We tentatively interpret these results in terms of age- and task-specific differences in the processing of the opportunity cost of time. We qualify our findings in a second experiment in younger adults in which we address an alternative explanation of our results and show that the observed age differences in effort expenditure may not result from differences in task difficulty.

To conclude, we think that our results present an interesting first step at relating opportunity costs to motivational processes across the lifespan. We frame the implications of further work in this area within a recent developmental model of resource-rationality, which points to developmental sweet spots in cognitive control.

## 1. Introduction

Humans possess an impressive arsenal of cognitive abilities in a variety of domains. Yet, these abilities are, in many cases, remarkably limited (Feng, Schwemmer, Gershman, & Cohen, 2014; Musslick & Cohen, 2019). Nevertheless, we engage in these processes because they seem to offer something of value. As a consequence, we face trade-offs between the cost (i.e., effort required) of engaging in a certain behaviour and its potential benefits. Whether and how we manage such trade-offs then depends on both our *ability* to complete these tasks, our available cognitive resources, as well as our *motivation* to do so.

However, individuals differ in their ability to succeed in these tasks. A substantial body of literature suggests that children and older adults have limitations in cognitive control abilities (e.g., Craik & Bialystok, 2006; Eppinger, Kray, Mecklinger, & John, 2007; Li, Hämmerer, Müller, Hommel, & Lindenberger, 2009; Munakata, Snyder, & Chatham, 2012). On the behavioral level these age-related limitations are reflected in reduced performance and slower reaction times in cognitive control tasks (Cepeda, Kramer, & Gonzalez de Sather, 2001; Kray, Eber, & Lindenberger, 2004; Zelazo, Craik, & Booth, 2004). On the neurobiological level, age differences in cognitive control abilities have been associated with developmental and aging-related changes in the

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<https://doi.org/10.1016/j.cognition.2021.104863>

Received 23 February 2021; Received in revised form 21 July 2021; Accepted 23 July 2021

Available online 9 August 2021

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function and structure of the prefrontal cortex (Braver & Barch, 2002; Bunge, Dudukovic, Thomason, Vaidya, & Gabrieli, 2002; Fjell & Walhovd, 2010; Kievit et al., 2014; Nyberg et al., 2010). Taken together, the current research suggests an inverted U-shaped pattern of cognitive control development across the lifespan: Control abilities increase during childhood development into early adulthood and then diminish in old age (e.g., Li et al., 2009).

While this “deficit-based” interpretation dominates the current literature, there also exist other, complimentary, explanations. One such account relies on children and older adults’ motivation, rather than ability alone. For example, it could be argued that performance differences between age groups in demanding cognitive tasks may reflect differences in cost-benefit analyses rather than limitations in cognitive abilities per se. That is, children and older adults might differ from younger adults not only in the cognitive and neurobiological mechanisms underlying cognitive control, but also in how they balance “cognitive labour” and “cognitive leisure” (Kool & Botvinick, 2014). First, children use cognitive effort assessments to guide their decisions and make metacognitive choices about effort investments from a young age (Chevalier, 2018). Second, while both young and older adults perceive cognitive effort as aversive, older adults are more sensitive to the cost that effort entails, which tends to exaggerate their aversion to expending effort (Hess, Smith, & Sharifian, 2016; Westbrook, Kester, & Braver, 2013). Importantly, a certain degree of cognitive abilities seems necessary as a prerequisite for such effort-reward balancing. For instance, in order to engage in metacognitive decisions about effort allocation children have to be cognitively able to perform the task to begin with (Blackwell & Munakata, 2014; Niebaum, Chevalier, Guild, & Munakata, 2019). The same might be said for older adults. Aging is characterized by deficits in various cognitive abilities (Bishop, Lu, & Yankner, 2010), which may affect their ability to perform a cognitive task and therefore shifts their effort-reward trade-offs (cf. Lieder & Griffiths, 2017).

In the present study, we explore how the moment-to-moment allocation of cognitive effort affects cognitive control and changes across the lifespan. To do so, we leverage theories of cognitive control and focus on two processes that are central to most of these theories: conflict processing and task-switching (Botvinick & Braver, 2015; Miller & Cohen, 2001).

Conflict processing refers to the ability to monitor task-appropriate behaviour, evaluate current levels of conflict, and exert top-down control to resolve these conflicts (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Yeung, 2015). Experimental paradigms that assess conflict processing require participants to inhibit distracting or dominant information in order to successfully perform the task. For instance, in the Eriksen Flanker task (Eriksen & Eriksen, 1974), participants are asked to identify a central letter (e.g., H) while ignoring flanking items (e.g., Ss). Incongruent Flanker trials involve crosstalk between task-relevant (respond to “H”) and task-irrelevant processing pathways (respond to “S”). This conflict is assumed to trigger effortful adjustments in cognitive control in order to optimize performance.

Task-switching requires a different, more complex set of control processes. While it also requires the exertion of top-down control, it involves implementing, maintaining, and updating task-relevant information while switching between two or more tasks (Monsell, 2003; Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004; Smith & Jonides, 1999). In a typical task-switching experiment (cf. Monsell, 2003), participants are asked to keep two task rules in mind (e.g., to judge whether numbers are even/odd or small/big). On each trial, they are told which rule they should use to complete this trial. These rules then either switch or repeat from trial-to-trial. The ability to update and maintain task-relevant information in order to be able to switch between tasks is assessed as switch costs that is, the difference in RT and accuracy between switch and repeat trials (Monsell, 2003).

Critically, both cognitive control processes require significant amounts of cognitive effort to accomplish. The degree to which an

individual allocates effort towards a cognitive control task therefore has important consequences for their performance. However, it has been a long-standing challenge in cognitive control research to quantify the degree to which effort exertion is modulated on a moment-to-moment basis. Nevertheless, doing so is necessary if we want to explore the effects that age-related differences in effort investment have on cognitive control. Therefore, to operationalize cognitive effort in the current study, we draw on Otto and Daw’s (2019) recent work, which elucidates cost-benefit decision-making concerning cognitive effort investment by manipulating the opportunity cost of expending cognitive effort. In line with their work, we refer to opportunity costs as the cost of using cognitive resources in service of some goal while forgoing the benefits of using it for some other goal (Kurzban, Duckworth, Kable, & Myers, 2013). Following Niv, Daw, Joel, and Dayan (2007) work on physical effort, we formalize cognitive trade-off between two costs: the harder work necessary to emit more correct actions and the opportunity cost inherent in acting more slowly to do so. In tasks that have a limited time horizon, opportunity costs can be thought of as the average reward per unit time. When average reward is high—when rewards are easy to come by—people tend to withdraw effort, which is reflected in higher error rates (Beierholm et al., 2013; Guitart-Masip, Beierholm, Dolan, Duzel, & Dayan, 2011; Otto & Daw, 2019). Such a withdrawal is driven by the fact that, when the reward rate of the environment is high, slowed responding incurs a larger opportunity cost, resulting in fewer trials completed and more high-reward opportunities foregone. In contrast, when average reward is low, such a constraint on responding is no longer present, and people invest relatively more effort into their judgements. Under this framework, accuracy can be thought of as the principal index of effort, whereas reward-induced differences in response times arise as an epiphenomenon of these effort assessments (Otto & Daw, 2019).

Accordingly, we hypothesized that differences in cognitive control abilities across the lifespan would be reflected in different sensitivities to the opportunity cost of time. Based on findings on individual differences in the effects of cognitive capacity on effort adjustments (Kool et al., 2010; Sandra & Otto, 2018), we predicted that, due to their constraints in cognitive capacity, children and older adults would be more sensitive to the opportunity cost of time than adolescents and younger adults. To study this hypothesis, we ran two experiments. In Experiment 1, we studied age differences in opportunity costs across the human lifespan using two cognitive control tasks: a Flanker task (Eriksen & Eriksen, 1974) and a task-switching paradigm (Monsell, 2003), both employing an average reward rate manipulation (for a similar procedure see Otto & Daw, 2019). Consistent with previous work (Otto & Daw, 2019), we found that young adults and adolescents withheld effort when the opportunity cost of time was high. In contrast to our prediction, older adults and (to a lesser degree) children invested more resources to accumulate reward. While our results did not straightforwardly map on to our initial predictions, we provide a theory-driven interpretation of these findings from a resource-rational perspective in terms of developmental “sweet spots” in cognitive control (Bejjanki & Aslin, 2020; Lieder & Griffiths, 2020; Ruel, Devine, & Eppinger, 2021). That is, we argue that the opportunity cost of time differentially modulates cognitive control based on characteristics of the task and the individual (i.e., age). We further qualify these results in Experiment 2, in which we manipulated task difficulty across the two paradigms for a new group of young adults. The results of Experiment 2 support this interpretation by demonstrating that differences in effort modulation according to the opportunity cost of time are due not only to task difficulty, but to genuine age differences in processing.

## 2. Experiment 1

### 2.1. Method

#### 2.1.1. Participants

We recruited 164 participants from the general public via the TU Dresden Lifespan Developmental Neuroscience participant database. Participants were paid a fixed amount (8.50 €/hour) plus a bonus dependent on their task performance. The sample size was determined based on previous lifespan studies on cognitive abilities (De Luca et al., 2003; Karbach & Kray, 2009; Störmer, Eppinger, & Li, 2014). The age range was constrained by minimal requirements for a separate decision-making task that participants completed as part of a task battery (results of which will be reported elsewhere). Participants (or, in the case of children and adolescents, their parents) underwent a telephone screening prior to participating. After exclusion (see Supplement), the final sample consisted of 144 participants: 49 children (Mage = 10.09, SD = 1.33, 21 males; 8–12 years old), 33 adolescents (Mage = 15.29, SD = 1.15, 14 males, 13–17 years old), 34 young adults (Mage = 23.72, SD = 4.48, 16 males; 20–35 years old), and 28 older adults (Mage = 70.66, SD = 5.03, 14 males, 57–78 years old).

In addition to the cognitive control tasks and the decision-making paradigm, participants performed two psychometric tasks from the domain of fluid intelligence (digit span and symbol search from the WISC-IV, Petermann & Petermann, 2011), and one from the domain of crystallized intelligence (the Spot-a-Word test, adapted from Lehrl, 1977 and the vocabulary test from the WISC-IV, Petermann & Petermann, 2011). The results of these tests are summarised in Supplemental Fig. 1. The results for the fluid intelligence tests showed the expected inverted U-shaped pattern across the lifespan (Craik & Bialystok, 2006; Li et al., 2004). The results for the crystallized intelligence tests showed an increase of word knowledge from childhood to adolescence and from young adulthood to old age. This is in line with previous findings suggesting stability or increase of crystallized abilities with age (Craik & Bialystok, 2006; Li et al., 2004). Taken together, the psychometric characteristics of the current sample are very similar to those of previous lifespan studies (Li et al., 2004; Störmer et al., 2014).

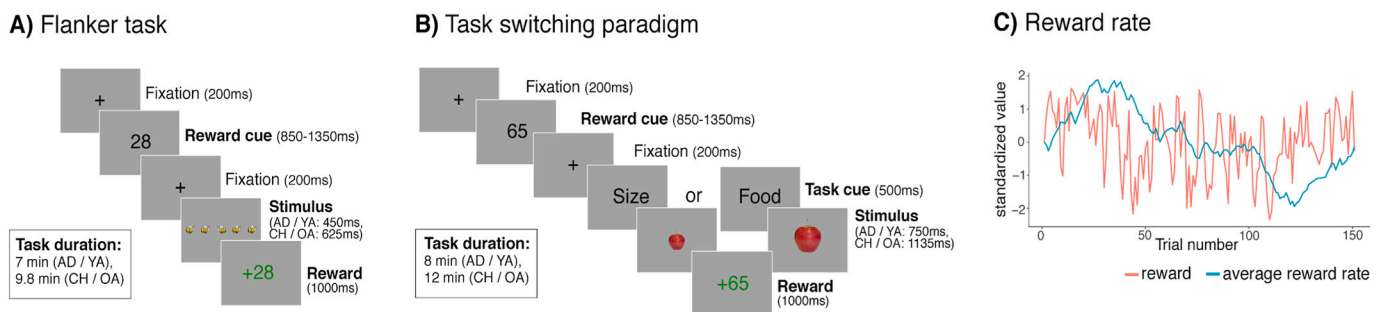
Participants/their legal guardians provided written informed consent prior to participation. This study was approved by the TU Dresden ethics committee.

#### 2.1.2. Materials

**2.1.2.1. Flanker task.** The Flanker task is a widely used measure of cognitive control (Eriksen & Eriksen, 1974; Fan, McCandliss, Sommer, Raz, & Posner, 2002). It requires participants to classify a target item, while ignoring distracting items that surround it. Distracting items can

either suggest the same response as the target item (congruent trials) or a different response (incongruent trials). On incongruent trials, participants must filter-out the distracting information from the flanking items, requiring the use of cognitive control (Enger, 2007).

In our version of the task (see Otto & Daw, 2019 for a similar methodology employing the Simon task [Simon, 1990]), participants had to indicate whether a bee in the center of the display was flying towards the left or to the right (see Fig. 1A). All stimuli were presented against a gray background using the software E-Prime (PST Inc., Pittsburgh, PA). Each trial began with a fixation cross presented for 200 ms. Then, a reward cue appeared that indicated how many points were at stake on that trial. The cue remained on the screen for a random amount of time chosen between the following options: 850 ms, 950 ms, 1050 ms, 1150 ms, 1250 ms, or 1350 ms. The reward on offer was worth between 5 and 95 points on each trial and participants were told beforehand that 100 points were worth 0.03 €. Available rewards were determined randomly using an independent Gaussian random walk with standard deviation 30 and with reflecting boundaries set at 6 and 96 points (non-inclusive). Following Otto and Daw (2019), this ensured that rewards were unpredictable from trial-to-trial and maximally uncorrelated from the average reward rate (see Fig. 1C). The stimulus display time (and therefore the response deadline) for younger adults was set to 450 ms in order to create some time pressure (Hübner, & Schüssler, J., 2010). To account for generally slower RTs in children and older adults, the stimulus display times were adjusted by a general slowing factor of 1.7. This slowing factor was based on a meta-analysis by Verhaeghen and Cerella (2002). Their findings suggest slowing factors of 1.6 (non-switch trials in a task switching task) to 1.8 (color naming in a Stroop task). Given the differences in tasks and task designs between our study and the ones reviewed in this meta-analysis we decided for 1.7 as an estimate of the expected slowing factors in the current tasks. This slowing factor seems consistent with the degree of slowing that can be estimated from the processing speed task mentioned above (1.48 in the old adults and 1.9 in the children compared to young adults, see Supplemental Fig. 1). In line with Verhaeghen and Cerella (2002) suggestions, we assumed a peripheral component to the reaction time of 200 ms and determined a stimulus presentation time of  $200 \text{ ms} + 250 \text{ ms} \times 1.7 = 625 \text{ ms}$ . For the purpose of this study we assumed that children and older adults show a similar degree of the reaction time slowing (see Li et al., 2004). This is clearly an oversimplification and it might be the case that there are process- and task-specific differences in RT slowing in the different age groups. Also, it is possible that due to differences in task difficulty between our study and ones reviewed in Verhaeghen and Cerella (2002) we might have overestimated the slowing factors and the deadlines applied in the current study were too liberal. We nevertheless opted for an adjustment of the stimulus presentation times in children and older adults because a deadline of 450 ms (as it was applied in younger adults)



**Fig. 1.** Task schematics for Flanker task and task-switching paradigm in Experiment 1, and visualization of reward and average reward for one participant. (A) In the Flanker task, participants have to indicate whether the bee in the center of the display is flying to the left or the right. On compatible trials the surrounding bees fly into the same direction. On incompatible trials they fly into the opposite direction. To account for slower RT in children and older adults we adjusted the stimulus display times (max response time). (B) In the task-switching paradigm, participants either indicated whether the object was a fruit or a vegetable (Food task) or they indicated whether it was small or large (Size task). To account for slower RT in children and older adults we adjusted the stimulus display times (max response time). (C) Example of reward magnitude and reward rate across the experiment for one participant in the Flanker task.

would have led to a disproportionate number of time-outs in these two groups, which would have made the results very difficult to compare.

Participants used two response keys to decide which direction the center bee was flying towards. If participants correctly identified which direction the center bee was flying, a green feedback message would appear showing them how many points they earned that trial. If they misidentified the direction, they would receive a red feedback message indicating that they had received no points this trial. This feedback message stayed on the screen for 1000 ms.

To manipulate opportunity costs, participants were told that they would have 7 min (for adolescents and young adults) or 9.8 min (for children and older adults) to complete as many trials as possible. Each participant had 10 trials to practice the task before beginning the.

main task. During this practice phase, participants were not under time pressure to respond. These practice trials were not included in the analyses.

**2.1.2.2. Task-switching paradigm.** Task-switching paradigms examine the flexibility with which a participant adapts their internal goal settings according to environmental changes. These paradigms require participants to adjust their internal task-rules, or task-sets, to changing task cues on a trial-to-trial basis and respond appropriately, a process which requires the use of cognitive control (Monsell, 2003).

In this version of the paradigm, participants were instructed to perform two tasks: the 'Food task' and the 'Size task' (see Fig. 1B). In the Food task, participants had to judge whether the stimulus on-screen was a fruit or a vegetable. In the Size task, they had to judge whether the stimulus on-screen was large or small. The stimulus set of this experimental task consisted of four foods: an apple, a pear, an eggplant, and a cucumber (taken from Moreno-Martinez & Montoro, 2012). Each food could be presented in one of two formats, in each trial: big (300 × 225 bitmap image file) or small (225 × 169 bitmap image file). All stimuli were presented against a white background on a standard PC using the software EPrime (PST Inc., Pittsburgh, PA).

In each trial, participants were presented with a fixation cross at the center of the screen for 200 ms. Then, a reward cue was presented that indicated how many points were at stake that trial. These rewards were initialized in the same way as in the Flanker task. The cue remained on the screen for a randomly determined amount of time (850 ms, 950 ms, 1050 ms, 1150 ms, 1250 ms, or 1350 ms) and was then followed by another 200 ms fixation cross. The task cue (Food or Size) was then presented on the screen for 500 ms (consistent with task switching experiments used in previous lifespan studies (Cepeda et al., 2001; Lawo, Philipp, Schuch, & Koch, 2012)). The stimulus was presented on the screen for 750 ms for young adults and adolescents and 1135 ms for children and older adults. Similar to the Flanker task we adjusted the stimulus presentation time to account for developmental and aging-related differences in overall reaction times using a slowing factor of 1.7 (Verhaeghen & Cerella, 2002). To do so, we assumed a peripheral component to the reaction time of 200 ms and determined a stimulus presentation time of 200 ms + 550 ms \* 1.7 = 1135 ms. As for the Flanker task, the motivation for adjusting the stimulus presentation times was to avoid disproportionate time pressure in children and older adults.

Participants used two response keys to decide if the stimulus was small/a fruit or big/a vegetable. If participants made the correct choice, a green feedback message appeared showing them how many points they earned that trial. If they misidentified the direction, they would receive a red feedback message indicating that they had received no points this trial. This feedback message stayed on the screen for 1000 ms.

To manipulate opportunity costs, participants were told that they would have 8 min (for adolescents and young adults) or 12 min (for children and older adults) to complete as many trials as possible. Each participant had 12 trials to practice the task before beginning the testing

phase. During the practice phase, there was no time pressure to respond. These practice trials were not included in the data analyses. At the end of the task, participants received 0.03 € for each 100 points they earned.

### 2.1.3. Procedure

On the testing day, participants underwent a task battery, in fixed-order, consisting of a basic demographic assessment, cognitive/intelligence testing, a measurement of spontaneous eye-blink rate, decision-making tasks, and the Flanker and task-switching paradigms. Participants in the older adult group additionally underwent the Montreal Cognitive Assessment (Carson, Leach, & Murphy, 2018). Here, we report data on the Flanker and task-switching paradigms; the data of the decision-making tasks will be reported elsewhere.

### 2.1.4. Data analysis

For all of the following analyses, all trials with a RT of less than 200 ms were excluded from analysis (based on recommendations from Whelan, 2008 regarding genuine RT minima). This decision impacted less than 1% of trials in the Flanker task and ~ 1% of trials in the task-switching paradigm. These proportions did not significantly differ across age groups in either task (Flanker:  $F(3, 140) = 1.433, p = .2358$ ; Task-switching:  $F(3, 140) = 1.56, p = .2024$ ). All analyses were conducted using R (Version 3.5.3; R Core Team, 2019).

**2.1.4.1. Descriptive analyses.** As is common in these types of cognitive control paradigms (Eppinger et al., 2007; Fan, Flombaum, McCandless, Thomas, & Posner, 2003), we computed compatibility costs and switch costs for RT and accuracy in both the Flanker task and task-switching paradigm by subtracting RT/accuracy in incongruent/switch trials from RT/accuracy in congruent/repeat trials. To account for differences in response deadlines, we measured performance in points per second for each participant. To explore how participants' overall performance differed across age groups, beyond differences seen in the RT and accuracy analyses, we conducted a one-way ANOVA with points per second as the dependent variable and age group as the independent variable. Statistically significant main effects were then explored using Tukey's honestly significant difference (HSD) post-hoc test.

**2.1.4.2. Average reward rate analyses.** Following past work, we calculated the average reward,  $\bar{r}$ , using the following update rule (Constantino & Daw, 2015; Otto & Daw, 2019):

$$\bar{r} = (1 - \alpha)^t \bar{r} + (1 - (1 - \alpha)^t) \frac{R}{t}$$

where  $R$  is the reward obtained on trial  $t$ ,  $T$  is the time elapsed since the last update, and  $\alpha$  is the learning rate parameter.  $\bar{r}$  was initialized as the average reward obtained across an entire session for each subject. From thereon,  $T$  relies on both the subject's last RT and the previous intertrial interval such that, everything else being equal, as the amount of time since the last update ( $T$ ) increases,  $\bar{r}$  decreases. Conversely, as the reward obtained,  $R$ , increases,  $\bar{r}$  increases. However, it is worth noting that average reward values are specific to each participant, thus between-participant differences in RT should not impact participants' sensitivity to them (e.g., such as differences found between age groups). This update rule allows for individual differences in the sensitivity to changes in  $\bar{r}$  beyond those seen to  $R$  alone (see Fig. 1C and D).

Following previous work (Beierholm et al., 2013; Guitart-Masip et al., 2011; Otto & Daw, 2019), the learning rate parameter,  $\alpha$ , was estimated by fitting a single-learning rate to the RTs of all participants within each age group. The learning rate can be thought of as controlling the degree to which the average reward estimate is updated based on the current outcome (Beierholm et al., 2013). This update rate could range between 0 (equivalent to no learning) and 1 (equivalent to only using the reward obtained in the previous trial). To estimate  $\alpha$ , we employed a grid search over the parameter space, estimating subject-specific



regressions within each age group in order to determine the value of the  $\alpha$  parameter that best minimized total error across the group (average squared residuals):

$$RT = \bar{r} + R + \text{trial type} + \text{prev type} + \text{prev error} + \text{prev missed} + \text{same resp} + ITI$$

where  $\bar{r}$  is the average reward rate,  $R$  is the reward magnitude on each trial, *trial type* is the type of trial the participant is to complete (congruent or incongruent for the Flanker task; repeat or switch for the task-switching), *prev type* is the trial type on the previous trial, *prev error* is a binary variable representing if the participant made an error on the previous trial, *prev missed* is a binary variable representing if the participant timed out (did not respond within the response deadline) in the previous trial, *same resp* is a binary variable representing if the participant repeated their response from the previous trial, and *ITI* represents the time interval between two updates (850 ms–1350 ms in steps of 100 ms). To ensure that this model was adequately specified—that is, that predicted RT distributions sufficiently matched empirical distributions in each age group—we ran a series of posterior predictive checks in each age group (see Supplement; cf. Wilson & Collins, 2019).

Using this technique, we found a best-fitting  $\alpha$  estimate of 0.0027 for young adults, which closely approximates the best-fitting  $\alpha$  observed by Otto & Daw (2019;  $\alpha = .0031$ ). For children, adolescents, and older adults, we found best fitting learning rates of 0.0200, 0.0010, and 0.0479 respectively. These values suggest that children and older adults used previous rewards to update current average reward more than adolescents and young adults. This lines up with past work demonstrating that children and older adults adapt their performance in cognitive control tasks to different reward magnitudes (Bolenz, Kool, Reiter, & Eppinger, 2019; Nussenbaum & Hartley, 2019).

With these learning rate estimates, we computed average reward rates for each subject. Mean reward rate values per age group were as follows. In the Flanker task, children had a mean average reward rate of 14.10 points per unit time (SE = 0.039), adolescents one of 15.54 (SE = 0.031), young adults one of 16.93 (SE = 0.030), and older adults one of 16.78 (SE = 0.056). In the task-switching paradigm, children had a mean reward rate of 9.93 (SE = 0.029), adolescents one of 11.27 (SE = 0.021), young adults one of 12.43 (SE = 0.018), and older adults one of 10.69 (SE = 0.056). Unsurprisingly, these values follow the same pattern as group performance levels, since  $\bar{r}$  is initialised at the average reward earned for one subject across a whole session. That being said, it is important to note that average reward as computed above and reward magnitude are not equivalent, the two only modestly correlating with each other ( $r_{\text{Flanker}} = 0.15$ ,  $r_{\text{TS}} = 0.18$ ; see Fig. 1C). This correlation varies across age groups in accordance with each group's estimated learning rate, with children and older adults having the strongest relationship between reward magnitude and average reward ( $r_{\text{Flanker-CH}} = 0.15$ ,  $r_{\text{Flanker-OA}} = 0.29$ ,  $r_{\text{TS-CH}} = 0.25$ ,  $r_{\text{TS-OA}} = 0.27$ ) and adolescents and young adults having the weakest ( $r_{\text{Flanker-AD}} = 0.03$ ,  $r_{\text{Flanker-YA}} = 0.04$ ,  $r_{\text{TS-AD}} = 0.003$ ,  $r_{\text{TS-YA}} = 0.02$ ).

To assess the effect of average reward rate on RT, we estimated mixed-effects regressions using the mixed function from the afex package in R (Version 0.23-0; Singmann, Bolker, Westfall, & Aust, 2015). The afex package is built on top of the lme4 package (Bates, Mächler, Bolker, & Walker, 2015), but has the added benefit of providing summary tables for main effects of multi-level (>2) predictors (such as age group in our case) and calculates  $p$ -values by using Satterthwaite estimation.

In both tasks, RT was modelled by age group (children, adolescents, young adults, or older adults), trial type (congruent/repeat or incongruent/switch), reward rate, reward magnitude, and all two-way, three-way, and four-way interactions as fixed effects, as well as random intercepts across participants (random effects). The terms of interest were the main effect of age.

group, trial type, and reward rate, as well as the interactions between

the three factors. All continuous variables were scaled and centered, except for RT, which was log-transformed across age groups as is common practice in research across the lifespan (e.g. Kray & Lindenberger, 2000). The effects of age group, trial type, reward rate, and reward were also examined using a logistic mixed-effects regression and the same predictors as for the RT analyses, but with response accuracy (correct/error) as the outcome variable.

## 2.2. Results

### 2.2.1. Flanker task

**2.2.1.1. Performance.** A one-way analysis of variance (ANOVA) showed a significant effect of age on performance (operationalized as points-per-second;  $F(3, 140) = 12.51$ ,  $p < .0001$ ), such that older adults ( $M_{\text{points/s}} = 1.58$ ), young adults ( $M_{\text{points/s}} = 1.57$ ), and adolescents ( $M_{\text{points/s}} = 1.46$ ) significantly outperformed children ( $M_{\text{points/s}} = 1.33$ ;  $p_{\text{older adults-children}} < 0.0001$ ;  $p_{\text{young adults-children}} < 0.0001$ ;  $p_{\text{adolescents-children}} = 0.043$ ) on a per-second basis, but differed only numerically from each other ( $p_{\text{older adults-young adults}} = 0.99$ ;  $p_{\text{older adults-adolescents}} = 0.100$ ;  $p_{\text{young adults-adolescents}} = 0.998$ ) (see Fig. 2A). These findings suggest that older adults performed at the same level as young adults and adolescents in the Flanker task. All three groups outperformed children.

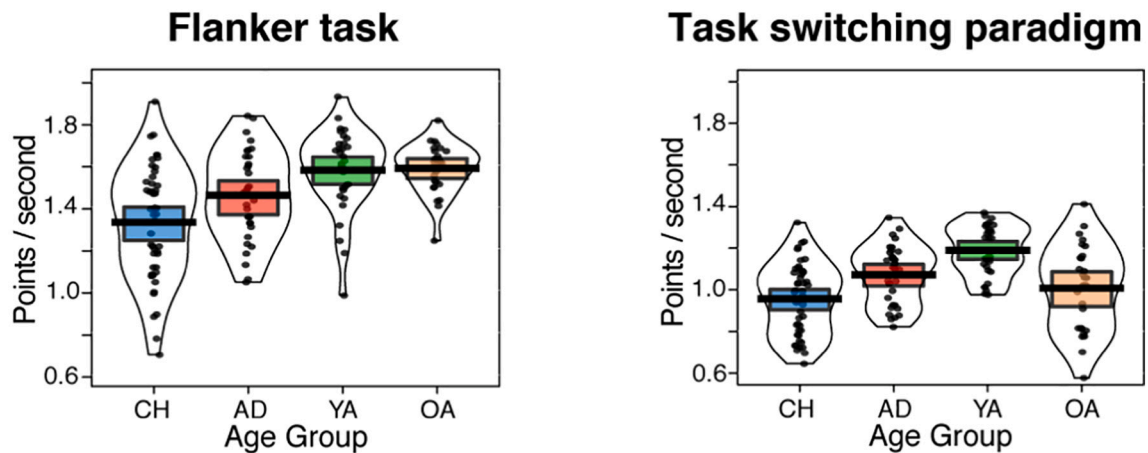
**2.2.1.2. Compatibility effects.** Mirroring past results (Erikson & Erikson, 1974; Ridderinkhof, Band, & Logan, 1999), we found a significant main effect of trial type on RT ( $\beta = -0.0132$ , SE = 0.0011,  $p < .0001$ ) and accuracy ( $\beta = 0.4307$ , SE = 0.025,  $p < .0001$ ), such that participants responded more slowly and less accurately on incongruent trials compared to congruent trials (see Supplemental Fig. 2). Additionally, we found a significant interaction effect between trial type (congruent or incongruent) and age group on both RT ( $F(3, 144.01) = 6.69$ ,  $p = .0003$ ) and accuracy ( $\chi^2(39) = 44.09$ ,  $p < .0001$ ). That is, all age groups responded more slowly ( $\beta_{\text{children}} = -0.0074$ , standard error (SE) = 0.0020,  $p = .0004$ ;  $\beta_{\text{adolescents}} = -0.0095$ , SE = 0.0027,  $p = .0012$ ;  $\beta_{\text{young adults}} = -0.0188$ , SE = 0.0023,  $p < .0001$ ;  $\beta_{\text{older adults}} = -0.0173$ , SE = 0.00216,  $p < .0001$ ) and less accurately ( $\beta_{\text{children}} = 0.2245$ , SE = 0.0278,  $p < .0001$ ;  $\beta_{\text{adolescents}} = 0.5441$ , SE = 0.0523,  $p < .0001$ ;  $\beta_{\text{young adults}} = 0.7126$ , SE = 0.06813,  $p < .0001$ ;  $\beta_{\text{older adults}} = 0.2968$ , SE = 0.0653,  $p = .0002$ ) on incongruent trials compared to congruent trials, but the magnitude of the compatibility effects differed across age groups with young adults showing the greatest compatibility costs in RT and adolescents showing the greatest costs on accuracy (see Fig. 3).

**2.2.1.3. Reward-on-offer effects.** We found a significant main effect of reward magnitude on RT ( $\beta = -0.0044$ , SE = 0.0010,  $p < .0001$ ), such that higher reward on offer engendered quicker RT.

However, we found no significant interaction of reward on offer with age group ( $F(3, 147.26) = 0.72$ ,  $p = .5442$ ). In line with Otto and Daw's (2019) findings, we found no significant main effect of reward on offer with accuracy ( $\beta = 0.0095$ , SE = 0.0224,  $p = .6698$ ) nor significant interaction with age group ( $\chi^2(3) = 3.55$ ,  $p = .3100$ ).

**2.2.1.4. Opportunity cost effects.** We found no significant main effect of average reward rate on RT ( $\beta = -0.0022$ , SE = 0.0014,  $p = .1106$ ) or accuracy ( $\beta = 0.0269$ , SE = 0.0262,  $p = .3301$ ). However, we found a significant interaction effect between age group and average reward rate on both RT ( $F(3, 131.80) = 2.88$ ,  $p = .0386$ ) and accuracy ( $\chi^2(3) = 12.99$ ,  $p = .0047$ ) (See Fig. 4). Follow-up analyses conducted within each age group revealed that average reward rate differentially affected participants' behaviour depending on their age. Specifically, changes in reward rate significantly predicted RT in older adults ( $\beta = -0.0079$ , SE = 0.0019,  $p = .0003$ ), such that when average reward was high, older adults responded more quickly. This effect was not found in any other age group.

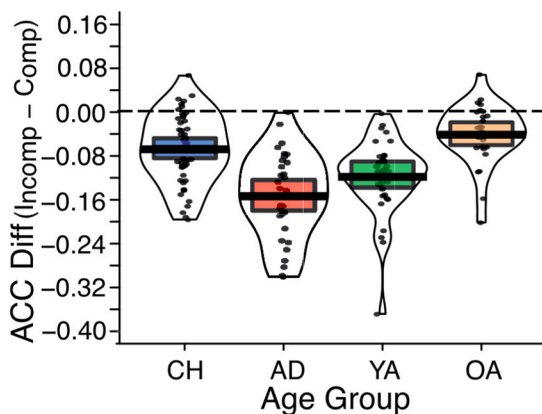
## Task Performance



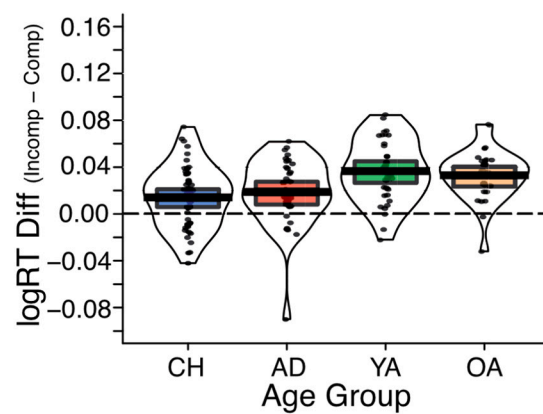
**Fig. 2.** Pirate Plots of performance across age groups in the Flanker task and task-switching paradigm. Coloured (shaded) boxes represent confidence intervals of the mean, black lines represent mean points per second of each age group, and black points represent individual participants' average points per second.

## Flanker task

### Accuracy compatibility cost

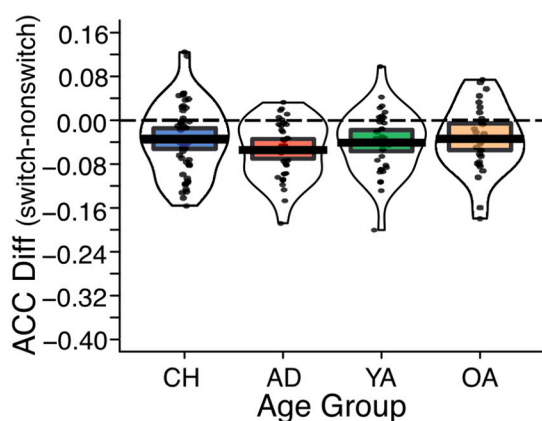


### RT compatibility cost

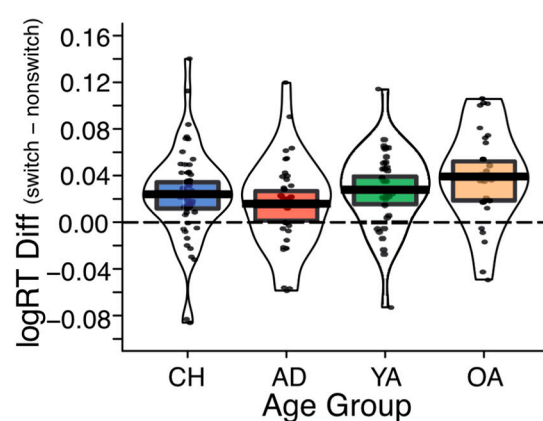


## Task switching paradigm

### Accuracy switch cost



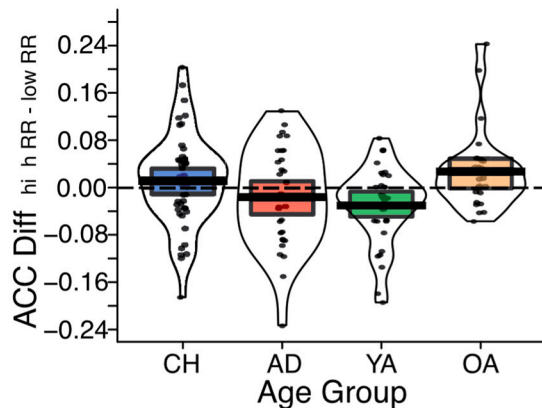
### RT switch cost



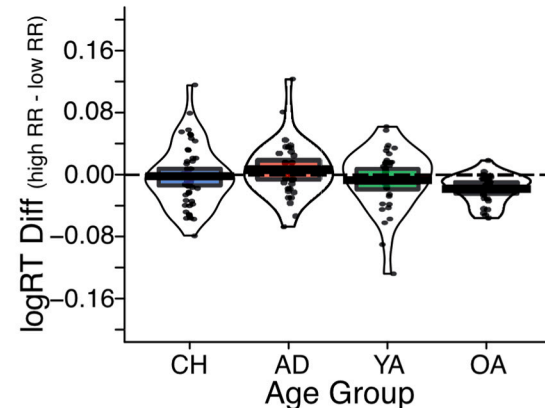
**Fig. 3.** Pirate Plots of difference scores for log-RT and accuracy in (A) the Flanker task and (B) the task-switching paradigms. Differences scores are computed by subtracting log-RT/accuracy in incongruent/switch trials by log-RT/accuracy in congruent/repeat trials. Coloured (shaded) boxes represent confidence intervals of the mean, black lines represent mean costs for each age group, and black points represent individual participants' costs.

## Flanker task

### Accuracy reward rate effects

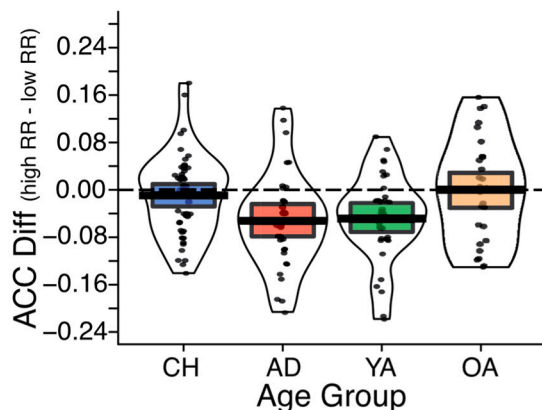


### RT reward rate effects

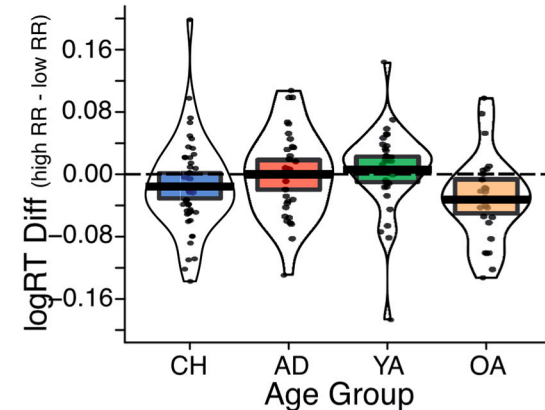


## Task switching paradigm

### Accuracy reward rate effects



### RT reward rate effects



**Fig. 4.** Pirate Plots of difference scores across the two tasks on (A) log-RT and (B) accuracy. Scores were computed by dividing reward rate into tertiles and dropping the middle quantile. Difference scores are represented here as “High - Low”, where High represents log RT/accuracy when reward rate is high and Low represents RT/accuracy when reward rate is low. For instance, a negative difference score in log-RT represents a speeding up during high reward rate trials. Coloured (shaded) boxes represent confidence intervals of the mean, black lines represent mean differences for each age group, and black points represent individual participants' reward rate effects.

Average reward rate was also found to significantly predict accuracy scores in older adults ( $\beta = 0.1605$ ,  $SE = 0.0734$ ,  $p = .0287$ ), such that when average reward rate was high, accuracy increased. In younger adults we found a trend in the opposite direction, such that when average reward rate was high, young adults became less accurate, but this effect was not statistically significant.

significant ( $\beta = -0.0903$ ,  $SE = 0.0492$ ,  $p = .0665$ ). We found no statistically significant effect of average reward rate on accuracy in children ( $\beta = 0.0652$ ,  $SE = 0.0413$ ,  $p = .1142$ ) or adolescents ( $\beta = -0.0231$ ,  $SE = 0.0387$ ,  $p = .5501$ ).

The current results suggest that in the Flanker task, older adults were more sensitive to changes in average reward rate both in terms of RT and accuracy than any other age group. When the reward rate was high, older adults responded more quickly and more accurately than when it was low.

### 2.2.2. Task-switching paradigm

**2.2.2.1. Performance.** A one-way ANOVA revealed a significant effect of age on performance ( $F(3, 140) = 14.92$ ,  $p < .0001$ ), such that young adults ( $M_{\text{points/s}} = 1.19$ ) outperformed children ( $M_{\text{points/s}} = 0.96$ ;  $p_{\text{young}}$

adults-children  $< 0.0001$ ), adolescents ( $M_{\text{points/s}} = 1.07$ ;  $p_{\text{young adults-adolescents}} = 0.018$ ), and older adults ( $M_{\text{points/s}} = 1.01$ ;  $p_{\text{young adults-older adults}} = 0.0001$ ). Furthermore, adolescents outperformed children ( $p = .009$ ), but did not differ significantly from older adults ( $p = .410$ ). Children and older adults did not differ in terms of performance ( $p = .5200$ ). As shown in Fig. 2, performance in the task-switching paradigm followed a U-shape function, where children and older adults performed worse than adolescents and young adults.

**2.2.2.2. Task-switching effects.** We observed a significant main effect of trial type on both RT ( $\beta = -0.0136$ ,  $SE = 0.0017$ ,  $p < .0001$ ) and accuracy ( $\beta = 0.1453$ ,  $SE = 0.0187$ ,  $p < .0001$ ), such that participants responded more slowly and less accurately on switch trials compared to repeat trials (see Supplemental Fig. 2). However, we did not find a significant interaction between age group and trial type on RT ( $F(3, 154.09) = 1.79$ ,  $p = .1521$ ) or accuracy ( $\chi^2(3) = 5.04$ ,  $p = .1691$ ) (see Fig. 3).

**2.2.2.3. Reward-on-offer effects.** We did not observe a significant main effect of reward on offer on RT ( $\beta = 0.0010$ ,  $SE = 0.0015$ ,  $p = .4943$ ) or

accuracy ( $\beta = 0.0111$ ,  $SE = 0.0197$ ,  $p = .5737$ ). Similarly, we observed no significant interaction of reward on offer with age group on RT ( $F(3, 777.11) = 0.51$ ,  $p = .6762$ ) or accuracy ( $\chi^2(3) = 0.16$ ,  $p = .9203$ ).

**2.2.2.4. Opportunity cost effects.** The analysis revealed a significant main effect of average reward rate on RT ( $\beta = -0.0049$ ,  $SE = 0.0022$ ,  $p = .03433$ ) and accuracy ( $\beta = 0.0110$ ,  $SE = 0.0197$ ,  $p = .0007$ ), such that participants responded more quickly, but less accurately when average reward rate was high compared to when it was low.

Additionally, we found a significant interaction effect between age group and reward rate on both RT ( $F(3, 148.76) = 3.94$ ,  $p = .0097$ ) and accuracy ( $\chi^2(3) = 16.25$ ,  $p = .0010$ ). Follow-up analyses revealed that reward rate differentially affected RT and accuracy in each age group. We found a significant effect of reward rate on RT for older adults ( $\beta = -0.0160$ ,  $SE = 0.00496$ ,  $p = .0032$ ), such that older adults responded more quickly when reward rate was high compared to when it was low. We also found a trend of reward rate on RT for children in the same direction as older adults, but that failed to reach statistical significance ( $\beta = -0.0074$ ,  $SE = 0.0038$ ,  $p = .05997$ ). We found no significant effect of reward rate on RT for adolescents ( $\beta = 0.0012$ ,  $SE = 0.0044$ ,  $p = .7894$ ) or young adults ( $\beta = 0.0038$ ,  $SE = 0.0042$ ,  $p = .3757$ ). In terms of accuracy, we did not find a significant effect of reward rate on accuracy in the children ( $\beta = 0.0004$ ,  $SE = 0.0326$ ,  $p = .9897$ ) or older adults groups ( $\beta = 0.0271$ ,  $SE = 0.072$ ,  $p = .7049$ ). However, we did observe this effect in adolescents ( $\beta = -0.1412$ ,  $SE = 0.0373$ ,  $p = .0002$ ) and young adults ( $\beta = -0.1957$ ,  $SE = 0.046$ ,  $p < .0001$ ), such that—for both of these groups—when average reward was high, accuracy scores decreased (see Fig. 4).

In summary, in the task-switching experiment, we found that changes in average reward rate predicted RT in older adults but not in adolescents or young adults. That is, older adults.

responded faster when the average reward was high compared to when it was low. We also observed a similar trend for this effect in children in the same direction, but it did not reach statistical significance. Conversely, changes in reward rate did not predict response accuracy in children or older adults, but did in adolescents and young adults. That is, adolescents and young adults responded less accurately on high reward rate trials compared to low reward rate trials, which was not the case in the other two age groups.

## 2.3. Discussion

In this experiment we explored how limitations in cognitive control abilities in different age groups might affect the moment-to-moment allocation of cognitive effort. We used a modified Erikson Flanker and a task-switching paradigm and manipulated the available reward for correctly responding on each trial. We hypothesized that the degree of effort exertion should depend on the opportunity cost of time. That is, we predicted that participants would withdraw effort when average reward was high (when reward were easy to come by) and that this should be reflected by reduced accuracy (Otto & Daw, 2019). We expected that age-related differences in cognitive control abilities would moderate the degree to which participants engaged in these strategies. Interestingly, we found that the opportunity cost of time affected behaviour differently in children and older adults than it did in adolescents and young adults.

### 2.3.1. Cognitive control costs

As shown in Fig. 3, we observed cognitive control costs in both the Flanker task and task-switching paradigm. Consistent with past work, we found that under higher demands on cognitive control (incongruent trials in the Flanker task and switch trials in task-switching paradigm) participants responded more slowly and less accurately (Eppinger et al., 2007; Fan et al., 2003). Furthermore, in the Flanker task, we found that trial type interacted with age group in both dependent variables, RT and

accuracy. That is, while all age groups showed the same direction of effects—slower and less accurate responses on incongruent trials—young adults and adolescents were the most affected by compatibility costs. This finding differs from past work that suggests that lifespan differences in conflict processing follow a quadratic function: with compatibility costs being highest in young childhood and late adulthood (Li et al., 2009). One reason for this deviation might be that we corrected for group differences in processing speed in our methodology, thus reducing cognitive control differences that may emerge as a result of overall slower reaction times in children and older adults (Manard, Carabin, Jaspard, et al., 2014; cite Verhagehen & Cerella, 2002). Another interpretation of this result could be that the average reward rate manipulation pushed children and older adults to respond more quickly and accurately overall, thus obscuring more extreme compatibility costs. A more extensive discussion of this shift in response strategies is provided in the next section.

### 2.3.2. Opportunity cost effects

In the Flanker task, we only found effects of the opportunity cost of time on cognitive control in older adults. That being said, we observed a rather different effect of opportunity cost on behaviour for older adults than we expected. Specifically, we found that older adults responded both *more* quickly and *more* accurately when the opportunity cost of time was high in the Flanker task. These results suggest that older adults processed the opportunity cost of time in the Flanker task differently than as described by Otto and Daw (2019): Rather than to withhold resources when the average reward was high, they invested more resources to accumulate reward as quickly as possible, which was reflected in higher accuracy. Thus, in the Flanker task, older adults seem to have taken a more rational cost-benefit approach to effort exertion, investing the most effort when rewards were most available (cf. Lieder & Griffiths, 2017). This strategy is in contrast to the reflexive, Pavlovian, withdrawal of effort that Otto and Daw (2019) observed in younger adults (Otto & Daw, 2019).

In the task switching paradigm, older adults responded more quickly when average reward was high and were therefore able to maximize the number of points they could earn per unit time. In contrast to the Flanker task, however, they were not able to improve accuracy and operated on the same performance level on high and low reward rate trials. Young adults and adolescents, on the other hand, responded less accurately, but not more quickly, when the opportunity cost of time was high. These findings are in line with the results obtained by Otto and Daw (2019) and their interpretation that the opportunity cost of time modulates effort investment beyond what would be expected of a simple speed-accuracy trade-off. That is, higher opportunity costs invoked a reflexive withdrawal of cognitive effort in adolescents and young adults, reflected in reduced accuracy, but did not lead to faster responses.

What about children? In the Flanker task, we found no effect of average reward on RT or accuracy for the children. In the task-switching paradigm however, we found a trend suggesting that children modulated effort in accordance with the opportunity cost of time similarly to older adults. However, this trend was not statistically significant ( $p \approx 0.06$ ). After observing this result, we hypothesized that the between group analysis might not be sensitive enough to show developmental changes in opportunity cost effects. Hence, we looked into the relationship between chronological age and opportunity costs on reaction time and accuracy (see Supplemental).<sup>1</sup> Here, we found again a trend, suggesting that younger children (less than 10 years old) invested more effort when average reward was high (similarly to older adults) whereas older children and young adults withhold effort when reward rate is

<sup>1</sup> In line with best practices regarding confirmatory hypothesis testing, we note that these analyses were exploratory and not based on original hypotheses. Instead, they were motivated by the non-significant trend we observed in the children as a group.



high. This might suggest that there are developmental milestones at which children modulate effort in accordance with the opportunity cost of time. This interpretation would be in line with recent discussions about developmental changes in effort-related metacognition that suggest that children begin to engage in adult-like effort-reward trade-offs by the age of 11 or 12 (Niebaum et al., 2019). The idea in this case would be that children with limited resources and metacognition (younger than 10) opt for simple heuristics adapted to their abilities: e. g., exert effort when reward is easy to come by. As children develop however, their behaviours begin to resemble that of adults, such that they ration out their resources to be utilized when rewards become less available.

To summarize, the findings of Experiment 1 suggest that children and older adults modulate effort investment according to the opportunity cost of time differently than younger adults and adolescents. Whereas young adults and adolescents reflexively withheld effort when the opportunity cost of time was high, older adults and (to a lesser degree) children invested *more* resources to accumulate reward as quickly as possible.

These age- and process-specific differences in the sensitivity to the opportunity cost of time are particularly interesting when we look at participant performance on the cognitive control tasks we administered. In the Flanker task, older adults unexpectedly performed (in terms of points/second and compatibility costs) at the same level as younger adults. In this way, our results differ from the typically observed inverted U-shape pattern found in life-span developmental studies on cognitive control (Li et al., 2009). We did observe such an inverted U-shape pattern in performance, however, only in the task-switching paradigm (Craik & Bialystok, 2006). This suggests that the strategic allocation of cognitive resources exhibited by older adults based on the opportunity cost of time may play a beneficial role in some (perhaps more basic) cognitive control processes, like conflict monitoring, but not necessarily in other (maybe more complex) processes, like task-switching (see Otto and Daw's (2019) discussion of speed-accuracy trade-off functions in task-switching). In line with this view, Flanker and task-switching tap into unique aspects of cognitive control, namely stability—the inhibition of distracting information—and flexibility—adaptation to changes in the environments—respectively. These facets of control are thought to trade off, such that increased flexibility comes at the cost of stability and vice-versa (Dreisbach & Fröber, 2019). Notably, the presence of rewards in the environment have previously been shown to influence this trade-off (Dreisbach & Fröber, 2019; Fröber & Dreisbach, 2014). It is thus possible that the average reward rate shifts this trade-off in a similar fashion, and that individual differences in sensitivity to average rewards—as seen between age groups in the current study—engenders unique patterns of stability and flexibility, as we see in differences in performance within the age groups, but between the Flanker and task-switching paradigm. The current experiment was not calibrated to test for these changes in stability versus flexibility directly, nor how they trade-off—doing so would require a single control task in which the same participants experienced changes in average reward the stability/flexibility of their behaviour was measured (e.g., the AX-CPT in Fröber & Dreisbach, 2014). That being said, such cognitive adaptation in accordance with the opportunity cost of time fits well with our general understanding of sensitivity to average reward as a rational adaptation to cognitive limitations (see General Discussion). Future work should endeavour to understand whether and how cognitive stability and flexibility trade off in a context where participants' responses are sensitive to the opportunity cost of time.

### 2.3.3. Limitations and considerations

An important question that follows from these results is why adolescents and young adults were only sensitive to the opportunity cost of time in the task-switching paradigm but not the Flanker task, whereas older adults were sensitive to reward rate in both tasks. Above, we offer the explanation that the opportunity cost of time affects behaviour not

only in an age-specific manner (in terms of *how* it affects reaction time and accuracy), but also in a process-specific manner. This interpretation lines up with past work that has shown that older adults differ from young adults both in terms of their overall cognitive control abilities, but also about how they use these limited resources to monitor conflict and flexibly adapt to changes in task contexts (e.g., Eppinger et al., 2007; Kray et al., 2005).

However, there is also an alternative explanation: one might suggest that the age differences we observe are not the result of age-specific sensitivities to the opportunity cost of time in conflict monitoring and/or task-switching, but are due to differences in perceived task difficulty. That is, older adults might have perceived the Flanker and task-switching experiments as more challenging and therefore invested more effort into the task. If this was the case, then different responses to the opportunity cost of time might *not* be an optimal adaptation to age- and task-related demands, but be due to differences in relative task difficulty alone. To examine whether variation in perceived demand could impact adaptation to average reward, we performed a follow-up experiment (Experiment 2) in younger adults only. Here, we aimed to manipulate task demand within younger adults to determine whether—when their control is heavily taxed—their responsibility to the average reward rate begins to resemble that of older adults; in other words, whether they begin to shift resource investment. If so, the observed age-differences in Experiment 1 may not reflect global differences in adaptation to age-related changes, but rather a more local adaptation to task demands: a subtle, but important distinction, from a lifespan development perspective. Accordingly, we predicted that if younger adults' cognitive control abilities were pushed closer to their limits—as we presumed they were for older adults in both tasks in Experiment 1—then they would exhibit similar opportunity cost effects as older adults.

## 3. Experiment 2

### 3.1. Method

We recruited 39 young adults through Concordia University's participant pool and were given participant pool credits plus a bonus depending on their task performance. This sample size was chosen to be able to compare the results to those of young adults in Experiment 1. All participants were English-speaking, free of neurological disorders, and free of any cognitive, motor, visual, or other condition(s) that would impede their performance, including but not limited to a history of head trauma with loss of consciousness, organic brain disorders, seizures, or neurosurgical intervention, to sensory deficits (i.e. deafness, blindness, color blindness, intellectual disability), or self-reported cognitive impairment. One participant was excluded from the analyses due to failing to meet the response deadline on a number of trials greater than 3SD from the mean in at least one task. The final sample was 38 young adults ( $M_{\text{age}} = 20.63$ ,  $SD_{\text{age}} = 1.82$ , 33 females). The study protocol was approved by the Concordia Human Research Ethics Committee.

#### 3.1.1. Materials

**3.1.1.1. Flanker task.** To manipulate task difficulty in the Flanker Task in Experiment 1, participants were pre-cued with flankers (without the target stimulus) before the presentation of each trial (Hübner & Töbel, 2019). These pre-cue flankers were either compatible (identical direction) or incompatible (opposite direction) to those being presented alongside the target stimulus. By presenting noise (i.e. the flankers) ahead of the target for a sufficient amount of time, we produced greater conflict with the target (Flowers, 1980).

We tested four different pre-cue durations (100 ms, 200 ms, 300 ms, 400 ms) to determine which would have the greatest effect on performance. Based on these preliminary analyses, the 100 ms pre-cue duration showed the largest decrease in performance as well as the greatest

compatibility costs (similar to the results of Hübner & Töbel, 2019). Participants each completed two blocks of this task: one with a 100 ms pre-cue and the second with no pre-cue (a control block identical to the Flanker task in Experiment 1). All other materials of the Flanker task were identical to those presented to young adults in the first experiment (see Fig. 5).

**3.1.1.2. Task-switching paradigm.** To manipulate task difficulty in the task-switching paradigm, we decreased the preparation time (time between the task cue onset and trial stimulus onset; 500 ms in Experiment 1). The logic of doing so is based on past work that demonstrates reduced switch-costs when information is given about the upcoming task—in effect, giving participants time to prepare for the following choice (i.e. preparation effect; Monsell, 2003). Similarly, when preparation time is increased, switch costs are more pronounced (Altmann, 2004; Schneider, 2016).

We tested four different preparation times (200 ms, 300 ms, 400 ms and 500 ms) to determine the one that would have the largest effect on switch costs. Based on these preliminary analyses, a 200 ms preparation time showed the greatest switch costs. Each participant completed two blocks of this task: one with a 200 ms preparation time and the other with a 500 ms preparation time (control block; see Fig. 5). All other materials of the task-switching paradigm were identical to those presented to young adults in the first experiment.

### 3.1.2. Procedure

On testing day, participants underwent a test battery, consisting of a categorization task (as part of another study), the Flanker task, and the task-switching paradigm. Participants completed the Flanker and task-switching paradigms in a counterbalanced order. All participants were given two blocks of each task (Flanker: 100 ms pre-cue and no pre-cue; Task-Switching: 200 ms and 500 ms preparation times), which were also counterbalanced within each task.

### 3.1.3. Data analysis

**3.1.3.1. Descriptive analyses.** All descriptive analyses were identical to those of Experiment 1, except that the age group variable was replaced by pre-cue duration and/or preparation time (in Flanker and task-switching paradigm respectively) in all analyses. Additionally, we conducted one-way ANOVA with RT and accuracy as dependent variables and pre-cue duration or preparation time as the independent variable to explore overall task performance.

**3.1.3.2. Average reward rate analyses.** Average reward rates were calculated in the same as in Experiment 1. In line with the results from

Experiment 1 and Otto and Daw (2019), we found a best-fitting  $a$  estimate of 0.0037 for young adults. The same regression models as in Experiment 1 were used to model the effect of average reward rate on RT and accuracy, substituting age group for task difficulty (pre-cue in flanker and preparation time in task-switching). The terms of interest were the main effect of task difficulty, trial type, and reward rate, as well as the interactions between these predictors on RT and accuracy.

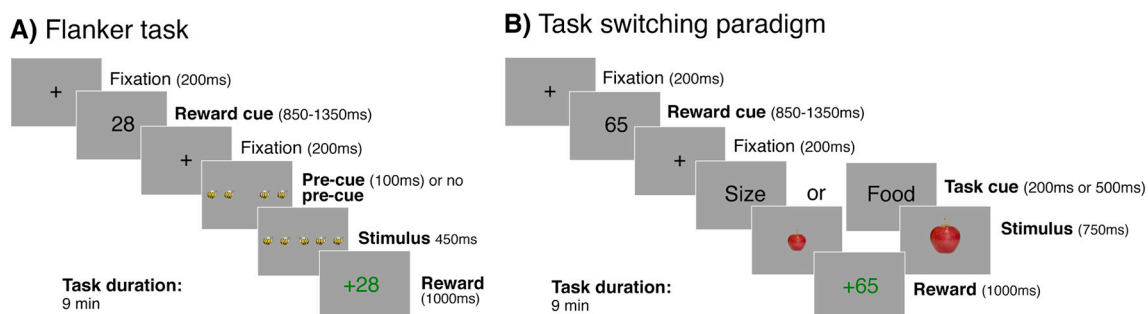
## 3.2. Results

### 3.2.1. Flanker task

**3.2.1.1. Performance.** A one-way analysis of variance (ANOVA) showed no significant effect of pre-cue on performance calculated as points per second ( $F(1,74) = 3.29, p = .074$ ). However, there was a main effect of pre-cue (0 or 100 ms) on RT ( $F(1,13,127) = 56.74, p < .001$ ; see Supplemental Fig. 3) and accuracy ( $F(1,13,127) = 27.46, p < .001$ ), whereby reaction times were longer ( $M_{diff} = 8.73, p < .001$ ) and participants were less accurate ( $M_{diff} = -0.016, p < .001$ ) in the 100 ms pre-cue block than in the no pre-cue block. This suggests that the 100 ms pre-cue block was overall more difficult than the block with no pre-cue.

**3.2.1.2. Compatibility effects.** We found a significant main effect of trial type on RT ( $\beta = 13.58, SE = 2.37, p < .0001$ ) and accuracy ( $\beta = -0.34, SE = 0.14, p = .00037$ ), such that participants responded more slowly and less accurately on incongruent trials compared to congruent trials. Additionally, we found a significant interaction effect between trial type and pre-cue on both RT ( $\beta = 18.79, SE = 2.13, p < .0001$ ) and accuracy ( $\beta = -0.61, SE = 0.17, p < .0001$ ). That is, there are significant compatibility costs in RT in both conditions (pre-cue, no pre-cue) in the expected direction (higher RT on incompatible trials). However, the compatibility costs were larger in the pre-cue than the no pre-cue condition (0:  $\beta = -13.58, SE = 2.37, p < .0001$ ; 100:  $\beta = -32.36, SE = 2.37, p < .0001$ ). Moreover, there are significant compatibility costs in accuracy in the 100 ms condition in the expected direction (lower accuracy on incompatible trials;  $\beta = 0.95, SE = 0.14, p < .0001$ ). Again, compatibility costs in accuracy were larger in the pre-cue than the no pre-cue condition ( $\beta = 0.34, SE = 0.14, p = .087$ ; see Fig. 6). Taken together, these results show that Flanker pre-cueing increases compatibility costs, suggesting that the task difficulty manipulation in the Flanker task was successful.

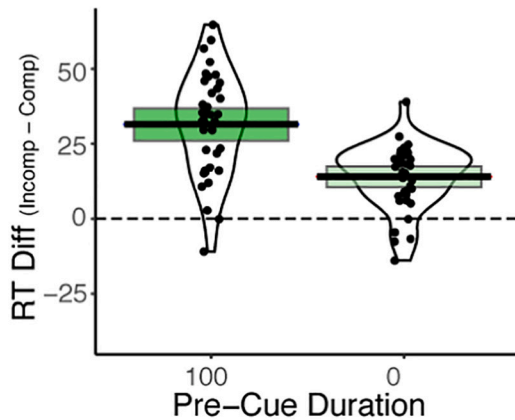
**3.2.1.3. Reward-on-offer effects.** We did not observe a significant main effect of reward on offer on RT ( $\beta = 0.78, SE = 1.06, p = .07642$ ) or accuracy ( $\beta = 0.052, SE = 0.096, p = .06274$ ). Similarly, we observed no significant interaction of reward on offer with pre-cue (none or 100 ms)



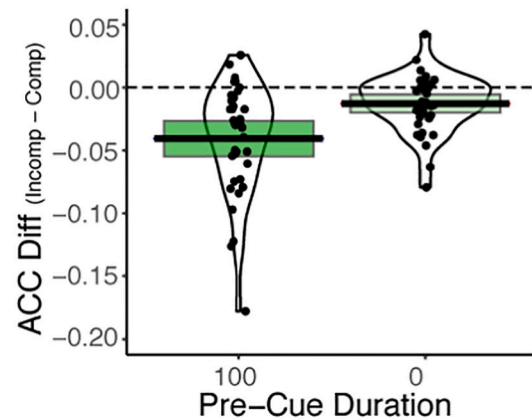
**Fig. 5.** Task schematics for the Flanker and Task-switching paradigm in Experiment 2. (A) In the Flanker task, participants have to indicate whether the bee in the center of the display is flying to the left or the right. On compatible trials the surrounding bees fly into the same direction. On incompatible trials they fly into the opposite direction. In one block we added a pre-cue of the flankers prior to the stimulus presentation. These flankers were either congruent or incongruent to those presented in the stimulus trial. (B) In the task-switching paradigm, participants either indicated whether the object was a fruit or a vegetable (Food task) or they indicated whether it was small or large (Size task). We manipulated the task cue time (or preparation time) in which participants had 1 block with a 200 ms preparation time and 1 block with a 500 ms preparation time.

## Flanker task

### RT compatibility cost

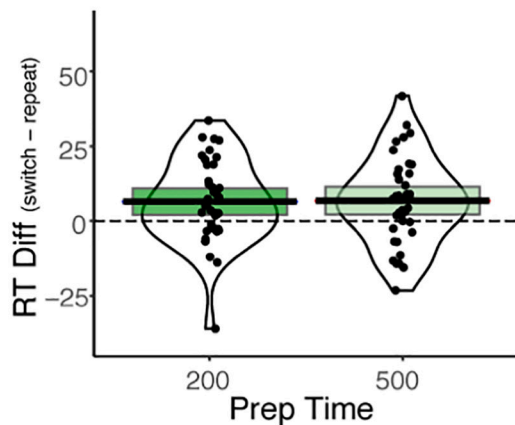


### Accuracy compatibility cost

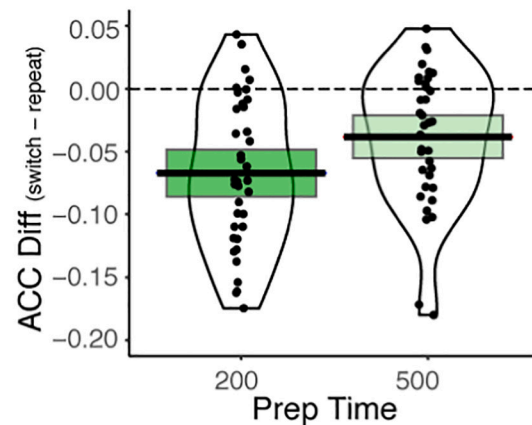


## Task switching paradigm

### RT switch cost



### Accuracy switch cost



**Fig. 6.** Pirate Plots of difference scores for RT and accuracy in (A) the Flanker task and (B) the task-switching paradigms. Differences scores are computed by subtracting RT/accuracy in incongruent/switch trials by RT/accuracy in congruent/repeat trials. Boxes represent confidence intervals of the mean, coloured lines represent mean costs for each age group, and coloured points represent individual participants' costs.

on RT ( $\beta = 7.06$ ,  $SE = 1.52$ ,  $p = .7980$ ) or accuracy ( $\beta = 0.016$ ,  $SE = 0.14$ ,  $p = .4626$ ).

**3.2.1.4. Opportunity cost effects.** We found no significant main effect of average reward rate on RT ( $\beta = -0.0032$ ,  $SE = 1.09$ ,  $p = .3044$ ) or accuracy ( $\beta = 0.089$ ,  $SE = 0.088$ ,  $p = .8176$ ). We also did not find a significant interaction effect between pre-cue and average reward rate on both RT ( $\beta = 0.49$ ,  $SE = 1.53$ ,  $p = .060$ ) and accuracy ( $\beta = -0.084$ ,  $SE = 0.13$ ,  $p = .2780$ ; see Fig. 7). Similar to experiment 1, these results show that in the Flanker task, young adults were not sensitive to changes in average reward rate neither in terms RT nor accuracy.

### 3.2.2. Task-switching paradigm

**3.2.2.1. Performance.** A one-way analysis of variance (ANOVA) showed no significant effect of preparation time on performance calculated as points per second ( $F(1, 74) = 0.30$ ,  $p = .59$ ; see Fig. 5B). However, preparation time (200 or 500 ms) did have an effect on RT ( $F(1, 11, 462) = 170.30$ ,  $p < .001$ ; see Supplemental Fig. 3) and accuracy ( $F(1, 11, 936) = 53.29$ ,  $p < .001$ ), whereby reaction times were longer ( $M_{diff} = 23.32$ ,  $p < .001$ ) and participants were less accurate ( $M_{diff} = -0.054$ ,  $p < .001$ ) in

the 200 ms preparation time block than in the 500 ms preparation time block. These results suggest that the difficulty manipulation was successful, producing slower and less accurate responding.

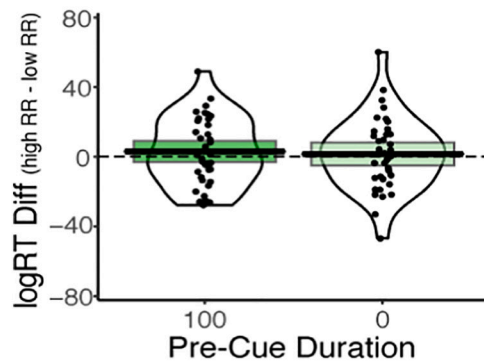
**3.2.2.2. Task-switching effects.** We observed a significant main effect of trial type (switch or repeat) on both RT ( $\beta = 6.79$ ,  $SE = 2.36$ ,  $p < .001$ ) and accuracy ( $\beta = -0.38$ ,  $SE = 0.063$ ,  $p < .001$ ), such that participants responded more slowly and less accurately on switch trials compared to repeat trials. However, we did not find a significant effect of preparation time on switch costs for RT ( $\beta = -0.0056$ ,  $SE = 3.36$ ,  $p = .9611$ ) or accuracy ( $\beta = 0.12$ ,  $SE = 0.093$ ,  $p = .1937$ ).

**3.2.2.3. Reward-on-offer effects.** We did not observe a significant main effect of reward on offer on RT ( $\beta = -0.56$ ,  $SE = 1.65$ ,  $p = .8819$ ) or accuracy ( $\beta = -0.0030$ ,  $SE = 0.045$ ,  $p = .7970$ ). Similarly, we observed no interaction of reward on offer with preparation time on RT ( $\beta = -0.31$ ,  $SE = 2.37$ ,  $p = .8689$ ) and accuracy ( $\beta = -0.056$ ,  $SE = 0.068$ ,  $p = .5602$ ).

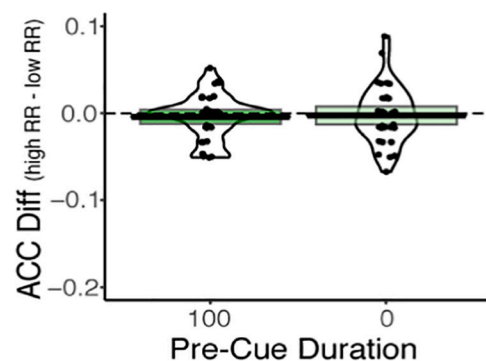
**3.2.2.4. Opportunity cost effects.** We found a significant main effect of average reward rate on RT ( $\beta = -4.04$ ,  $SE = 1.72$ ,  $p = .01029$ ) and

## Flanker task

### RT reward rate effects

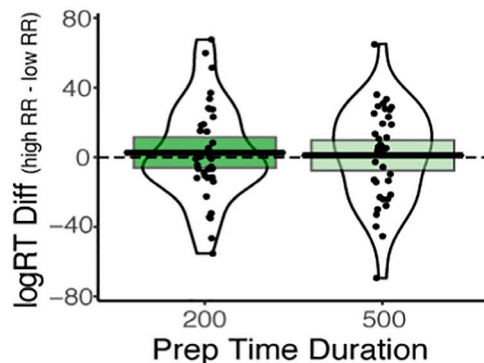


### Accuracy reward rate effects

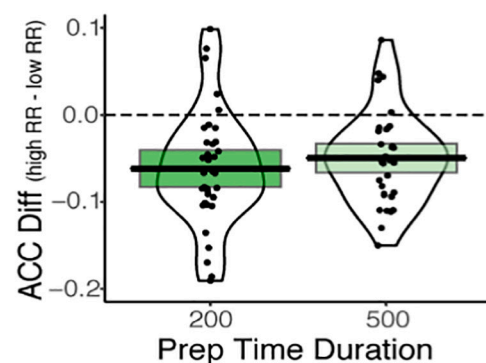


## Task switching task

### RT reward rate effects



### Accuracy reward rate effects



**Fig. 7.** Pirate Plots of difference scores across the two tasks on (A) RT and (B) accuracy. Scores were computed by dividing reward rate into tertiles and dropping the middle quantile. Difference scores are represented here as “High – Low”, where High represents RT/accuracy when reward rate is high and Low represents RT/accuracy when reward rate is low. For instance, a negative difference score in RT represents a speeding up during high reward rate trials. Boxes represent confidence intervals of the mean, coloured lines represent mean differences for each block (pre-cue or preparation time), and coloured points represent individual participants' reward rate effects.

accuracy ( $\beta = -0.03$ ,  $SE = 0.047$ ,  $p = .03718$ ), such that participants responded more slowly and less accurately when average reward was high, suggesting a withdrawal of effort. However, it is worth noting that while a statistically significant RT difference was observed overall, this difference was extremely small (average difference between low and high reward rate responses = 0.0543 ms; see Fig. 7). Furthermore, we found no significant interaction between preparation time and average reward rate on either RT ( $\beta = 2.55$ ,  $SE = 2.43$ ,  $p = .9001$ ) or accuracy ( $\beta = 0.035$ ,  $SE = 0.067$ ,  $p = .08588$ ). The current results suggest that in the task-switching paradigm, young adults were sensitive to changes in average reward rate in terms of accuracy (reduced accuracy when reward rate is high, similar to Experiment 1) and negligibly in terms of RT.

### 3.3. Discussion

The main goal of this experiment was to address a possible alternative explanation to our results in Experiment 1. Namely, that children and older adults experienced the cognitive tasks as more challenging than younger adults and therefore invested more effort.

To test this hypothesis, we performed a follow-up experiment in younger adults only and manipulated task difficulty. We predicted that if

younger adults' cognitive control abilities were pushed closer to their limits, they would show similar opportunity cost effects as older adults in Experiment 1. As before, we hypothesized that the degree of exertion of cognitive effort should depend on the opportunity cost of time—operationalized as the average reward per unit time—whereby young adults would respond less accurately when average reward was high compared to when it was low (Otto & Daw, 2019). Additionally, however, we hypothesized that this relationship would be mediated by task difficulty, such that when young adults had less time to prepare (task-switching) or were presented with additional, irrelevant, information (Flanker pre-cue), they would expend more effort when the opportunity cost of time was high (as older adults did in Experiment 1).

In both tasks, we replicate the basic pattern of results in younger adults from Experiment 1, despite the fact that we increased task demands (see Fig. 6). We found that young adults did not modulate effort according to average reward in the Flanker task, but withdrew effort when average reward was high in the task-switching paradigm. Overall then, the results from this follow-up experiment provide further evidence for the idea that young adults modulate effort according to the opportunity cost in a *process-specific* manner and reflexively withhold resources when rewards are cheap (when the reward rate is high). In other words, the results support the view that there exist genuine age



differences in how individuals modulate cognitive effort over time and that these differences cannot simply be explained in terms of task difficulty.

#### 4. General discussion

The purpose of this study was to explore how age-related differences in cognitive control abilities affect effort cost-benefit trade-offs across the lifespan. We hypothesized that cognitive effort would be exerted in accordance with the opportunity cost of time (the average reward rate) and that the degree to which it would be exerted would depend on participants' age. In Experiment 1, we found that the opportunity cost of time differentially affected behaviour in children, adolescents, younger, and older adults. Namely, we found that while adolescents and young adults exhibited a reflexive, Pavlovian, withdrawal of effort when the opportunity cost of time was high (less accurate responding, but no change in RT), older adults and, to some extent children, expended effort to accumulate reward (faster RT and better or unchanging accuracy when average reward rate was high). Furthermore, we found that while older adults applied this strategy to cognitive control tasks more broadly, children, adolescents and younger adults seemed to selectively apply it to the task-switching paradigm.

We qualified this interpretation of age- and process-specific sensitivity to opportunity cost of time by addressing an alternative explanation of the data in Experiment 2; namely that differences in responses to the opportunity cost of time were driven by relative task difficulty. To this end, we predicted that increased task difficulty would shift younger adults' use of the opportunity cost of time towards the pattern of results obtained in older adults (greater accuracy and slower RT on high compared to low reward rate trials). Our findings did not support this alternative explanation, however. We found that young adults responded in the same way as Experiment 1, even when their cognitive resources were further taxed.

What can we take away from this, admittedly, complex pattern of results? When rewards were cheap, adolescents and young adults withheld cognitive resources. In contrast older adults and, to some degree children, expended cognitive effort when rewards were easy to come by. At first glance, it may seem as if the behaviour in older adults is suboptimal: they expend resources when they should be saving them for when rewards become less available. However, our results could also be interpreted from a resource-rational perspective (Lieder & Griffiths, 2020). Under this model, people develop optimal heuristics for maximizing expected reward *conditional upon* internal (available cognitive resources) and external (the task at hand) factors. In other words, optimality under this framework is contingent on internal and external constraints and different agents' approaches may be equally optimal despite differences in both process and outcome. When applied to developmental differences then—where children's and older adults' decisions are commonly held to be deficient in some way—a resource-rational approach is a powerful tool for breaking free from the view that children and older adults are somehow cognitively “sub-optimal” (see Bejjanki & Aslin, 2020). We argue that older adults (and possibly children) are being resource-rational in their allocation of cognitive resources, choosing to expend their limited resources when it confers immediate benefit.

More specifically, we relate the current results to recent theoretical work that suggests humans solve control problems in a resource-rational manner (Lieder & Griffiths, 2017, 2020). Under this view, an agent adaptively adopts a problem-solving strategy that optimizes performances relative to the constraints placed on them by the system and/or the environment. Though originally derived to explain strategy selection (Lieder & Griffiths, 2017), this framework has since been extended to cognitive control, wherein an agent must determine the optimal way to invest a limited pool of cognitive resources to solve control problem, such that the costs of the computations required to engage in control do not outweigh the expected benefits said control promises (Lieder,

Shenhav, Musslick, & Griffiths, 2018). To do so, agents must both correctly predict the costs of control and the expected benefits.

A resource-rational framework for solving control problems is a powerful tool for understanding age-related differences in strategic effort investment that supplements, without supplanting, previous work on age-related deficits in cognitive ability (see Persaud, Bass, Colantonio, Macias, & Bonawitz, 2020; Ruel, Devine, & Eppinger, 2021). To wit, we propose that such a resource-rational account of cognitive control can account for the observed findings in the current study via what we call resource-rational “sweet spots” (see also Ruel, Devine, & Eppinger, 2021 for a more detailed account of this theory based on past literature). The idea here is that individuals' behaviours are differentially affected by the opportunity cost of time based on (a) their age (and associated cognitive limitations) and (b) what type of cognitive control process is needed to accomplish a task. We argue that individuals of different ages develop optimal heuristics that maximize reward rate relative to internal cognitive constraints and the external (environmental) demands. For young adults, who's resources are bountiful, such a heuristic might be to withhold resources until they are needed (i.e., when rewards become sparse), as it requires relatively little effort to reap the rewards in high reward environments. For older adults and children on the other hand, the heuristic might be to “get in when the getting is good”, expending resources where they are able to acquire maximum reward. Thus, older adults' and children's heuristics may not be suboptimal when compared to young adults'. Rather, both approaches are tailored to individuals' abilities and task demands. It is in this sense that we speak of a “sweet spot” model, where different tasks may trigger different cognitive processes that lead people to optimal engagement in metacognition (Ruel, Devine, & Eppinger, 2021.; for a very similar *satisficing* model in the realm of belief updating, see Bruckner, Nassar, Li, & Eppinger, 2020).

Similar instantiations of these age-specific cost-benefit sweet spots have been observed in a recent study on the flexible adaptation of decision-making strategies: While older adults show reduced sensitivity to cost-benefit evaluations when adjusting their reliance on different decision strategies in a multi-stage decision task, these same participants adapt their performance in cognitive control tasks to different reward magnitudes (Bolenz et al., 2019; Ruel, Devine, & Eppinger, 2021). Furthermore, our findings join work in demonstrating that older adults broadly allocate resources to even simple cognitive control tasks (Friedman, Nessler, Cycowicz, & Horton, 2009). Generally speaking, this broad and unspecified allocation of resources is thought to result in poorer cognitive control among older adults (Friedman et al., 2009). In contrast to this work however, we contend that such allocation can be rational, strategic, and even result in increased performance, as seen in the Flanker task. In other words, such behaviour can be optimal, from a resource-rational perspective.

Our view differs from deficit-based accounts (e.g., Braver & Barch, 2002; West, 1996), which posit that older adults' limitations in cognitive control result *solely* from functional and structural decline in the prefrontal cortex. Rather, we suggest that older adults may strategically balance their more limited cognitive resources to make boundedly optimal metacognitive decisions. In this study, we argue that this balancing is reflected through their sensitivity to the opportunity cost of time, whereby older adults mobilize cognitive resources in situations where the costs of inaction were high—i.e., opportunity costs are high; the average reward rate is high. It is important to emphasize, however, that these accounts do not suggest that cognitive limitations do not play a role in how individuals engage in these trade-offs. On the contrary, we believe that as cognitive resources begin to develop or decline in childhood and old age respectively, humans seem to adaptively allocate them in accordance with the opportunity cost of time. Therefore, our view aims to supplement “deficit-based” interpretations (and indeed assumes their truth to some degree), rather than to supplant them. Thus, our work can be seen as a step towards developing a lifespan developmental theory that formalize the dependencies between process-specific cognitive limitations and effort allocation. We believe the results of the

current study add important specification in this regard, as they demonstrate a pattern of lifespan developmental differences in the moment-to-moment engagement of cognitive control that conforms to a resource-rational model and a sweet spot account of metacognitive developmental decision-making. That being said, there is an obvious need for more research in this area. In particular, future studies should focus on more extreme age ranges while considering the process-specificity of these trade-offs and manipulating task demands (see more below).

To summarize, our findings join a spate of recent work that suggests that older adults *can* make optimal metacognitive decisions about cognitive resource allocation, *despite* structural limitations and declines (Ruel, Devine, & Eppinger, 2021; Ferdinand & Czernochowski, 2018; Yee, Adams, Beck, & Braver, 2019; Patzelt, Kool, & Gershman, 2019; Harsay, Wijnen, Guerreiro, & Ridderinkhof, 2010; cf. Lieder & Griffiths, 2020; cf. Bejjanki & Aslin, 2020). In the current study, we demonstrate that one way such bounded optimality is achieved is by tracking and allocating resources in accordance with the opportunity cost of time.

#### 4.1. Deviations, limitations, and future directions

It is important to note where the current results deviate from past work. First, our results differ in one important way from Otto and Daw (2019). In current study, young adults were not sensitive to the opportunity cost of time in the Flanker task. In contrast, Otto and Daw (2019) found, in the general population, significant opportunity cost effects in a Simon task, a conflict processing task structurally similar to the Flanker task. One reason for this divergence in results might be that the paradigms assess different types of conflict. The Flanker task applied in our study primarily assesses stimulus-driven conflict and it has been argued that conflict effects in the Flanker task may actually reflect stimulus-driven priming processes (Mayr, Awh, & Laurey, 2003). In contrast, the Simon task primarily taps into response conflict (for a discussion see Botvinick, 2007). This interpretation is in line with the general conclusion of the current study regarding the process-specificity of the opportunity cost effects.

Second, we did not observe reliable effects of reward-on-offer on either RT or accuracy. This runs counter to previous control literature that has found evidence for increased effort investment when cognitive control is incentivized (Frömer, Lin, Wolf, Inzlicht, & Shenhav, 2021; Kool & Botvinick, 2014; Otto & Vassena, 2021), but is consistent with Otto and Daw's (2019) results, which employed a similar opportunity cost manipulation. In that work, the authors propose that the opposing predicted effects of high reward-on-offer versus high average reward—the former encouraging resource investment and the latter withdrawal—may counteract each other, effectively contravening the effect of reward. Another explanation may relate to the task dynamics themselves and their relation to participants' ability to track average reward. Future work may seek to investigate whether interfering with this ability (e.g., by increasing the interval between trials, effectively reducing time spent exerting effort) would reduce average reward effects and increase reward-on-offer effects. Indeed, we find some support for this view, such that the reward effects in the Flanker task in Experiment 2 approach, but did not reach statistical significance.

In addition to these deviations, this study has several important limitations that need to be considered. First, the total time on task in Experiment 1 differed between age groups. This was a necessary feature of our design to account for overall longer reaction times in children and older adults, which would have led to an overabundance of timeouts in these age groups (when using the same deadlines; see Salthouse, 2000; Kiselev et al., 2009; Fry & Hale, 2000). While important, this design feature also engenders confounds between the age groups which may have affected how they processed the opportunity cost of time (or perceived the task overall, see the point above). This limitation is partially addressed in Experiment 2 however, as the young adults in this experiment experienced two difficulty conditions back-to-back (within-

subjects design). In both cases, they showed a similar pattern of responding as they did in Experiment 1, despite a greater total time on task. It is worth noting however that the sample of young adults in Experiment 2 may have provided an imperfect proxy for the group differences in performance in Experiment 1—a caveat worth keeping in mind when interpreting these results.

Second, our sample's developmental age range was constrained with lower bound at age 8 years. As discussed earlier, there is reason to believe that the sensitivity to the opportunity cost of time follows a developmental pattern, such that younger children expend effort when average reward rate is high (like older adults), but learn over time (across development) to withdraw it (like the adolescents and young adults). This interpretation remains speculative however. Future research should try to provide a more fine-grained analysis of the developmental trajectories in younger children.

Third, our sample did not include any middle-aged participants (36–56 years old). This would have been necessary to explore lifespan developmental trajectories while treating age as a continuous variable. In addition, this would have increased power and eliminated the need to artificially bin participants in age groups. Furthermore, it would have qualified the findings we observed in the older adults, such that we could have explored changes in the sensitivity to the opportunity cost of time as a function of changes in cognitive abilities from young adulthood to older age.

## 5. Conclusion

Overall, our results point to age- and process-specific sensitivities to the opportunity cost of time. That is, we find that older adults (and to a lesser degree children) expend cognitive effort to accumulate reward when the opportunity cost of time is high, whereas adolescents and younger adults withdraw effort. These interpretations remain speculative for now, as the current work has a number of limitations which constrain the generalizability of its results. Nevertheless, we believe these results represent an interesting first step towards understanding how motivational processes develop across the lifespan from a resource-rational perspective. To wit, we argue that the current results suggest that children and older adults can optimally allocate cognitive resources to strategically adapt to cognitive control demands in their environment. We contend that one way such allocation is made is in accordance with the opportunity cost of time.

### Declaration of Competing Interest

The authors declare no conflict of interest.

### Data availability

Raw data for all tasks in both experiments are available at: <https://osf.io/jb49t/>

### Credit author statement

S.D. analyzed the data, co-designed Experiment 2, provided the main theoretical interpretation, wrote the initial draft of the manuscript, incorporated co-author feedback, and served as corresponding author during the publication process.

C.N. designed, recruited participants for, and partially analyzed data for Experiment 2. She also drafted important sections of the manuscript and provided critical feedback.

A.R.O. assisted with the implementation of the computational modeling, provided theoretical insight, and gave critical feedback throughout the writing process.

F.B. helped to design, analyse, and collect data for Experiment 1, as well as provided important feedback on the manuscript.

A.R. collected the majority of the data for Experiment 1 and provided

important feedback on the manuscript.

B.E. supervised and funded the project, helped design Experiment 1 and 2, co-drafted the original manuscript with S.D., and provided indispensable theoretical insight throughout data analysis and the writing process.

## Acknowledgements

This work was supported by a grant from the German Research Foundation (DFG) [SFB 940/2 B7] as well as the Natural Sciences and Engineering Research Council of Canada (NSERC), [funding reference number N01882]. Furthermore, this research was undertaken, in part, thanks to funding from the Canada Research Chairs program. The authors thank Annekathrin Rättsch, David Reindel, Theresa Kolb, Noemi Holz, Johanna Dicke, Alexander Nitsch, Lion Schulz, and Niclas Lemmer for their assistance with data collection, as well as all participants and parents for taking part in the study.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cognition.2021.104863>.

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