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Resource-rational approach to meta-control problems across the lifespan

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Abstract

Over the last decade, research on cognitive control and decision-making has revealed that individuals weigh the costs and benefits of engaging in or refraining from control and that whether and how they engage in these cost–benefit analyses may change across development and during healthy aging. In the present article, we examine how lifespan age differences in cognitive abilities affect the meta-control of behavioral strategies across the lifespan and how motivation affects these trade-offs. Based on accumulated evidence, we highlight two hypotheses that may explain the existing results better than current models. In contrast to previous theoretical accounts, we assume that age differences in the engagement in cost–benefit trade-offs reflect a resource-rational adaptation to internal and external constraints that arise across the lifespan.

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KEYWORDS

children, cognitive control, decision-making, meta-control, older adults

1 | INTRODUCTION

When trying to solve a complex goal-directed task such as navigating to a restaurant in a new city, we can apply different types of strategies (or combinations of strategies). We can learn the layout of the new city from a map and then use this knowledge to reach the restaurant, or we can simply put the address in our navigation device (GPS) and let it guide us there. For we can engage in either strategy or a combination of both, we are left with a meta-control problem: we have to decide which strategy (or combination thereof) to engage in based on the expected outcomes and the effort each one requires. In the example above, most people would engage in the simple and less effortful strategy of using a navigation device. However, there are scenarios in which we might have a long-term interest in developing an internal representation of a cognitive map of the city (e.g., becoming a resident of the city) and might therefore decide to engage in the more effortful strategy. In these cases, one must balance the immediate costs of engaging in effortful activity (the time spent committing the city layout to memory) against the benefits such activity confers (a more flexible and rapid navigation in the future).

In this manuscript, we examine how individuals of different ages solve the cost–benefit trade-offs that may arise when different behavioral strategies are available to perform a given task. We assume that constraints in cognitive capacity (as commonly observed in children and older adults) are one important determinant of how such trade-offs are solved. We start by describing how cost benefit trade-offs are studied using cognitive control and decision-making paradigms and examine the performance of younger adults in these tasks. We then consider what is known about developmental and aging effects on the engagement in these trade-offs. Specifically, we review how age-related differences in cognitive abilities affect the meta-control of behavioral strategies across the lifespan. Finally, we consider how motivational factors such as incentives may shift these cost–benefit analyses in different age groups. We conclude by presenting two hypotheses to explain age differences in the meta-control of behavioral strategies. These theoretical accounts assume that age differences in the engagement in cost–benefit trade-offs reflect a resource-rational adaptation to internal and external constraints in children and older adults.

2 | TRADE-OFFS IN COGNITIVE CONTROL

Cognitive control requires the encoding and maintenance of task representations and has been suggested to rely on a set of basic cognitive abilities, consisting of both working and episodic memory as well as attentional functions (Cattell, 1987; Salthouse, 1990; Willis & Marsiske, 1991). Many activities of daily life (such as navigating to a specific restaurant in a new city, to return to an earlier example) require the efficient engagement and maintenance of such control to achieve one's goal. Yet, sustained engagement in cognitive control (i.e., continuously engaging in cognitive effort toward a goal) is effortful, and therefore, similarly to physical effort, tends to be aversive (Botvinick, 2007; Botvinick & Braver, 2015; Kool et al., 2010; Kool, Shenhav, & Botvinick 2017). As a consequence, we often choose to refrain from engaging in cognitive control and instead engage in simpler, habitual, strategies that may be suboptimal in terms of performance, but are cognitively cheaper to perform (Botvinick, 2007; Botvinick & Braver, 2015; Kool et al., 2010, 2017).

Therefore, how we solve this meta-control problem depends on how much value we attribute to the outcome of a chosen strategy as well as the cost that it entails. For example, take a classic variant of the Ericksen flanker task (Eriksen & Eriksen, 1974) in which participants must decide if a central stimulus is pointing left or right. Flanking this center stimulus is a set of similar stimuli that either point in the same direction as the center stimulus (congruent) or opposite to it (incongruent). The difficulty of the incongruent trials is evidenced by behavioral deficits such as reduced accuracy and slower reaction times (Eriksen & Eriksen, 1974). Throughout the task then, participants must engage in cognitive control to monitor conflict and to inhibit incongruent information when it arises. To incentivize maximal engagement in such control, variants of the Flanker task provide a small monetary incentive for each correct response participants make (see Hsieh et al., 2010). In other variants, rewards fluctuate across trials (Devine et al., 2020; see Figure 1(a)). In these cases, participants are presented with a meta-control problem: either to invest resources into sustained control to maximize performance and reward, or to reduce control and risk foregoing potential gains. To resolve this problem, individuals typically engage in a cost–benefit analysis, investing more control when costs are offset by higher rewards as shown in a study by Kool et al. (2010). The authors demonstrate that participants tend to avoid cognitive effort when rewards are unchanged, yet when rewards are increased, their avoidance is reduced due to these benefits offsetting the costs of effort. Alternatively, participants may decide that the value of the reward is (subjectively) insufficient to offset the costs associated with cognitive control and instead default to simple, less cognitively demanding control strategies. These subjective computations have been empirically demonstrated by Westbrook et al. (2013) who used a paradigm in which participants choose between two tasks: (1) a low effort task which provides small monetary rewards or (2) a high-effort task which returns larger rewards. Participants made several choices, and the amount offered for the low-effort task was adjusted until subjective equivalence between both tasks is reached. The authors found that equivalence was achieved when the low-effort task was associated with a significantly lower monetary reward as compared to the rewards associated with the high-effort task. Thus, participants were motivated to engage in effortful control up to a certain point, showing a clear quantification of how humans trade reward for effort. Several other effort-based control tasks have been employed to show that individuals engage in these cost–benefit analyses regarding the choice to engage in cognitive control. These include Stroop-like attention tasks (Padmala & Pessoa, 2011), free recall memory tasks (Libby & Lipe, 1992), and stop-signal tasks (Leotti & Wager, 2010) among others.

Interestingly, these cost–benefit analyses are also represented in the brain. For instance, work by McGuire and Botvinick (2010) has shown that lateral prefrontal cortex (PFC) activity correlates with individual differences in effort-based choice with greater activation reflecting a stronger avoidance of cognitive effort. Furthermore, support for the dissociation of costs and benefits at the neural level comes from findings by Basten et al. (2010) who reveal that the ventromedial and left dorsolateral PFC seem to compute the expected costs and benefits as they receive signals for these computations from the amygdala and ventral striatum, respectively. Finally, more recent work by Shenhav et al. (2013)

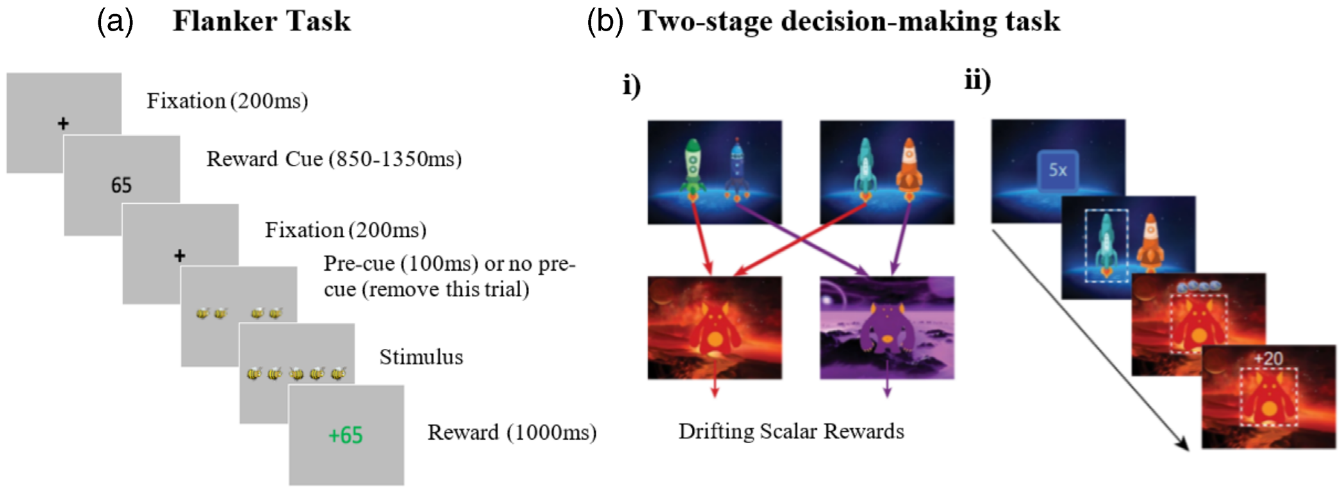

FIGURE 1 (a) Schematic figure of the Flanker task. In this paradigm, participants have to indicate whether the center bee is flying to the left or right. On congruent trials, the flanking bees are flying in the same direction. On incongruent trials, the flanking bees fly in the opposite direction. Before each trial, a reward cue which indicates how many points can be obtained if the correct response is given is shown on the screen (adapted from Devine et al., 2020). (b) Schematic figure of the modified two-stage decision-making task. (i) Each trial begins with one of two possible states in which participants must decide between different pairs of spaceships which allows them to transition to either of two second-stage states (i.e., a red vs. purple planet). The relationship between spaceships and planets is deterministic. Each planet hosts a single alien delivering fluctuating rewards which slowly changes on a trial-by-trial basis. (ii) At the start of each trial, participants are presented with a reward multiplier indicating if points on that trial would be multiplied by 1 (low stake trials) or 5 (high stake trials). Reprinted from Kool, Gershman, and Cushman (2017)

reveals that these signals are integrated in the dorsal anterior cingulate cortex (dACC), helping the individual determine whether and how much control to allocate in a given context.

3 | TRADE-OFFS IN DECISION-MAKING

Such meta-control problems are not specific to cognitive control processes. They are also encountered in the context of learning or decision-making. In many real-world situations (e.g., navigating to a restaurant in the city), we can engage in two choice strategies of different complexities. The first consists of simple habitual strategies that rely on previous experiences of similar decisions, such as using a habitual route. The second refers to elaborate goal-directed strategies that involve forward planning, such as considering all possible routes in order to select the one with the shortest transit time. In the reinforcement learning (RL) literature, these strategies are referred to as model-free (MF) and model-based (MB) learning, respectively. MF decision-making is computationally inexpensive as it relies on learned action-outcome associations, whereas MB learning is computationally expensive as it involves the mental simulation of candidate actions based on a learned internal model of the task (see Daw et al., 2011). When faced with the choice to engage in different decision-making strategies, individuals weigh the approximate cognitive effort required for each strategy against the expected value of the decision outcome and prioritize the action that maximizes reward. Furthermore, depending on the rate of change (volatility) of the environment, the optimality of this choice may be subject to reevaluation over the course of the task. Consequently, it has been proposed that the arbitration between MB and MF strategies is achieved by integrating the approximate costs and benefits of each strategy, similar to the analysis of costs and benefits associated with engaging in cognitive control (Kool et al., 2017, 2018).

In their recent work, Kool et al. (2018) have tried to capture such arbitrations using a variant of a two-stage Markov decision task (see Daw et al., 2011, Figure 1(b)). In this task participants can either engage in a MF strategy that relies on learned action-reward associations or they can adopt a MB strategy that also accounts for the probabilistic transition structure that connects the two stages of the task. Critically, in their variant of the paradigm, reward cues of different magnitudes are provided at the beginning of each trial to induce cost–benefit trade-offs (see Figure 1(b)). The results of this study show that participants demonstrate greater MB decision-making on trials with larger compared to smaller reward incentives. In other words, subjects engaged in cost–benefit trade-offs when making meta-control decisions about cognitive resource investment, such that they only engaged in MB control when the benefits of doing so outweighed the costs. Similarly, Kool et al. (2018) assessed whether people adjust their degree of MB decision-making as the complexity of required planning was manipulated. Across three experiments, they found that the allocation of MB decision-making was proportional to the degree of planning demands associated with it.

4 | COGNITIVE CONTROL AND DECISION-MAKING: TWO SIDES OF THE SAME COIN

In the last two sections, we discussed how individuals engage in cost–benefit trade-offs when solving meta-control problems. Despite the apparent differences between the two, our decision to engage in a more or less effortful behavioral strategy seems to be governed by a similar process: namely, an effort-reward cost–benefit trade-off. How can this relationship be understood from a theoretical perspective? Several models have been proposed that summarize and elucidate decades of research on motivation and control.

5 | THEORETICAL MODELS EXPLAINING THE RELATIONSHIP BETWEEN MOTIVATION AND COGNITIVE CONTROL

5.1 | Reward-based models

One of the leading theoretical approaches explaining the relationship between motivation and control focuses on the theme of reward maximization. Reward-based models frame control as involving a series of decisions made with the aim of maximizing utility. These decisions weigh both the anticipated rewards as well as the expected costs of engaging in such effort; resulting in a cost–benefit analysis in which the value of the reward is discounted by the amount of cognitive effort that needs to be exerted. Dixon and Christoff (2012) support this hypothesis, and demonstrate that participants rarely decide to engage in cognitive control when the outcome of doing so is equal or less than the reward given for choosing the task that requires no cognitive effort. Yet, participants frequently choose to invest resources into control when it is expected to result in a large reward.

5.1.1 | Expected value of control model

A closely related reward-based model, the expected value of control model (EVC model), integrates the expected reward (e.g., monetary gain), the amount of control required to obtain the reward, and the cost in terms of cognitive effort (Shenhav et al., 2013). The cumulative reward expected after engaging in control with a particular intensity is subtracted from the cost of the exertion itself. These cost–benefit analyses guide decisions which are made in order to optimize EVC. Work by Kool and Botvinick (2014) support this model by demonstrating that decisions to engage in cognitive control come from weighing both income and leisure (i.e., lack of cognitive effort). Specifically, they find that wage reductions lead to a decrease in cognitive effort to settle for a smaller reward, while wage increases lead participants to give up leisure—engaging in more effort to obtain the promised reward.

5.2 | Opportunity cost of time

Another account incorporates a closely related cost: time. The opportunity cost of time holds that the cost of effort also depends on the rewards that are being foregone in order to obtain the current (anticipated) outcome. That is, because the brain has limited resources, we must not only choose to engage in control based on immediate reward, but also based on what anticipated actions and rewards will be foregone by engaging in control now instead of later (Kurzban et al., 2013). Thus, in contrast to the previous models, the opportunity cost of time also considers *when* it is most beneficial for a participant to engage in cognitive control based on remaining resources as well as the costs and benefits of doing so. Also grounded in RL, this model defines the trade-off as the weighting of two costs. First is the effort assumed necessary to produce faster actions (e.g., responding faster on a Stroop task) and second is the opportunity cost inherent in acting more slowly, in which case there is a delay in getting to the next rewards (usually resulting in less monetary gain by the end of a fixed time task). In other words, the opportunity cost of time is the average reward rate per unit time (Beierholm et al., 2013; Niv et al., 2007). A study by Otto and Daw (2019) leveraged recent theories on the opportunity cost of time to examine how manipulating the average reward rate affects young adults' decisions to engage in cognitive effort. They found that subjects tuned their level of effort to the average reward rate. When the opportunity cost of time was high, participants made more errors and responded more quickly as compared to when the opportunity cost of time was lower. Due to the perceptual nature of the decision-making task, responding faster meant that participants accumulated less evidence before making a response which resulted in reduced accuracy, but also led to a reduction in the cost associated with accumulating more evidence. This pattern of behavior is consistent with the conclusion that when the opportunity cost of time is high, participants withdraw cognitive effort.

Uniting these theories is a set of explicit assumptions (see Box 1). However, an implicit assumption of these models is that they consider value and costs to be stable across participants. So far in this paper, we have treated effort as a variable that is determined by the characteristics of the task, while ignoring important task-independent individual differences that affect effort investment. For instance, structural and/or functional limitations in brain function may reduce ones' ability to engage in cognitive control or in a MB decision strategy. This should lead to steeper discounting

Box 1 Formalizing theories of cost–benefit trade-offs

The models presented above share a common set of assumptions, based in computational theories of RL:

1. The brain has limited computational resources that can be invested toward a task at any given time.
2. Investing these resources at one time point depletes them for later use.
3. The investment of these resources is dictated by an optimization function that aims to maximize rewards and minimize costs.
4. Control is costly, but can yield high rewards.

While these models share these basic assumptions, they differ in how they formalize them. The reward-based model (Dixon & Christoff, 2012) suggests the following:

$$\text{Value}\,(\text{control}_i) = \text{Expt.Reward}\,(\text{control}_i) - \text{Expt.Costs}\,(\text{control}_i), \tag{1}$$

where the value of engaging in cognitive control at time i is proportional to the rewards expected from doing so, adjusted for the costs inherent in mobilizing the necessary resources.

The EVC model makes a similar claim but is probabilistic and summative in nature,

$$\text{EVC}\,(\text{signal}_i, \text{state}_i) = \left[\sum_i p(\text{outcome}_i | \text{signal}_i, \text{state}_i)\,\text{value}\,(\text{outcome}_i)\right] - \text{cost}(\text{signal}_i), \tag{2}$$

where the expected value one could obtain from engaging in control is a function of the probability of obtaining reward if resources are mobilized, adjusted for the costs of doing so. Thus, control is only engaged in when EVC is positive; that is, in all probability, the benefits outweigh the costs.

Finally, opportunity cost models posit that control is invested in accordance with the average reward per unit time, which can be formalized as follows:

$$\bar{r}_{i+1} = (1-\alpha)^\tau + \bar{r}_i + (1-(1-\alpha)^\tau)\frac{R_i}{\tau}. \tag{3}$$

Here, the average reward per unit time is updated each time point i based on τ, the time since the last update, which depends on participants' engagement and is reflected in response time, and α, a free learning rate parameter. R here represents the reward magnitude at time point i.

functions; whereby expected rewards will be more heavily adjusted for by increased processing costs. In what follows we will consider how age-related cognitive limitations affect such meta-control processes across the lifespan.

6 | COST–BENEFIT TRADE-OFFS ACROSS THE LIFESPAN

Inverse U-shaped developmental curves have been found for several basic cognitive processes such as attention, memory, and inhibition (see Kail & Salthouse, 1994; Li et al., 2013). That is, just as basic cognitive processes have been shown to improve from childhood to adulthood, they have been shown to follow the opposite pattern, decreasing with increasing age. Thus, as one ages, the amount of cognitive control an individual can successfully harness will vary at the individual level but more importantly according to age-related changes in cognitive resources.

Cognitive control and MB decision-making performance seems to peak in young adults. Moreover, behavioral control is bolstered even further when young adults are provided with greater incentives (e.g., money) for higher performance (Kool et al., 2018; Padmala & Pessoa, 2011). In line with the theories presented in the last section, it seems that incentives serve as an additional benefit in young adults' cost–benefit analysis, making it worthwhile for them to engage in greater control. In the domain of decision-making, consistent with the outcome of a cost–benefit analysis, participants demonstrate more MB decision-making on trials with larger incentives, but only when it leads to better performance on the task (i.e., greater benefits, often meaning more money; Kool et al., 2017).

In contrast to younger adults, children and older adults likely compute these cost–benefit analyses differently due, in part, to their reduced cognitive abilities.

6.1 | Children

To study effort reward trade-offs in children, Chevalier (2018) asked children to perform a cognitive effort discounting paradigm which allowed for the estimation of how much reward children were willing to forgo in order to conserve cognitive effort. Children aged 7–12 years avoided harder tasks, not due to their lower likelihood of success or motivation, but due to the additional effort the task required. Specifically, children at this age already require significant incentive to perform more difficult N-back tasks (e.g. 2-back vs. 1-back) (Chevalier, 2018). Using a demand selection task (see Kool et al., 2010), in which participants must make a recurring choice between two tasks that each varied in cognitive demands, findings by Niebaum et al. (2019) echo those by Chevalier (2018). Specifically, Niebaum et al. (2019) show that 11–12-year-olds, like adults, exhibit a significant preference for selecting the less demanding task. In contrast, younger children (6–7-year olds) do so only when provided with feedback and explicitly instructed to select the easier task. In line with these findings, when provided trial-by-trial feedback and familiarization with each task before making a choice, 5-year-old children have been shown to demonstrate the slight ability to discriminate between task difficulties (O'Leary & Sloutsky, 2017). Similarly, when younger children (i.e., 5–7-year-olds) were encouraged to monitor their performance by estimating their own feedback, they performed better on a flanker task than children who received no feedback as well as better than children who received standard feedback (Hadley et al., 2020). That is, when children were encouraged to keep track of their performance (which encourages metacognitive reflection), their performance improved. In line with these findings, training metacognitive refection seems to lead to longer lasting benefits, showing improvements in working memory even 3 months after training (Jones et al., 2020), and even in children as young as 5 years (Pozuelos et al., 2019). These results suggest that metacognitive reflection may be a key for efficient cognitive control engagement.

Together, it seems that adaptive meta-control of behavioral strategies emerges with development between the ages of 10 and 13 years. Interestingly, this is consistent with the developmental trajectory of brain areas involved in the ability to flexibly integrate learned associations between stimuli, events and contexts (i.e., PFC; Menon et al., 2005; Ofen et al., 2012; Shohamy & Turk-Browne, 2013; Zeithamova et al., 2012), the implementation of cost–benefit analyses (i.e., dorsolateral anterior cingulate cortex or dACC; Shenhav et al., 2013) and the avoidance of cognitively demanding tasks (i.e., connectivity between PFC and dACC; Shenhav et al., 2013, 2017).

As children develop the ability to adapt to demands in control via cost–benefit trade-offs, they also start to increase cognitive effort if the incentive motivates them enough to respond. For instance, Strang and Pollack (2014) found that children (9–11 years old), adolescents (14–16 years old), and adults all demonstrated a shift to greater cognitive control when provided with greater rewards. In contrast, findings by Insel et al. (2017) revealed that participants aged between

13 and 18 years performed similarly across high and low value trials on a go/no-go task. Nevertheless, participants who demonstrated an enhanced performance on high-stake trials showed greater connectivity between the ventral striatum and the ventrolateral PFC which has been implicated in the maturation of cognitive control, RL and value-based decision-making (Insel et al., 2017). Together, their findings suggest that adolescents show clear neural evidence of the engagement in cognitive control yet continue to show improvements as they mature. Even children as young as five have recently been shown to demonstrate greater MB learning, but only on an age-appropriate task in which MB decision-making outperformed MF learning (Smid et al., 2020). Yet, incentivizing more complex decision-making tasks reveals that with increasing age, adolescents show greater adaptation of MB decision making to outcome magnitudes (Bolenz & Eppinger, 2020). Thus, it seems that meta-control continues to develop into young adulthood.

Overall, the sensitivity and ability to adapt to cognitive control and demands on MB learning appear to emerge with development alongside metacognitive abilities, allowing children as young as 11–12 years old to engage in adult-like cost–benefit trade-offs. Yet, costs still loom larger from childhood through adolescence, often resulting in a preference for habitual strategies. Furthermore, due to sharp differences in findings using different tasks (e.g., cognitive control tasks versus decision-making tasks), these developmental changes may also be task-dependent.

6.2 | Older adults

A considerable body of work demonstrates that cognitive control declines in aging adults (Mayr et al., 2001; McDowd & Shaw, 2000). In a conflict monitoring task, older adults demonstrate greater difficulties in cognitive control showing greater conflict costs than younger adults (Li et al., 2009). Similarly, in task switching experiments, older adults tend to show larger interference effects than younger adults (Eppinger et al., 2007) and demonstrate significant difficulties selecting between task sets (Kray et al., 2004). Furthermore, subjective perceptions of task difficulty vary on an individual level and seem to incorporate aspects of task demands as well as experience of their own efforts during the completion of the task, increasing the perceived demands of cognitive control (Westbrook et al., 2013). Consequently, as costs loom greater, older adults typically err on the side of caution, engaging in habitual responses instead of cognitive control or MB decision-making following a cost–benefit analysis (Hess et al., 2016; Westbrook et al., 2013).

Nevertheless, recent work has shown that for specific tasks, the excessive cautiousness with which older adults approach cost–benefit trade-offs can be mitigated by motivational incentives, leading to an upregulation of control. For instance, older adults can attain motivation-related performance enhancements in tasks that require cognitive control. Although their responses slow down, they seem to do so to maintain accuracy, allowing them to engage in more cognitive control (Starns & Ratcliff, 2010; Yee et al., 2019). In contrast to cognitive control, motivational incentives do not seem to lead to increased MB decision-making in older adults, even when engaging in this more complex strategy leads to better task outcomes (Bolenz et al., 2019; Patzelt et al., 2019). Thus, it seems that the reduced MB learning seen in older adults cannot be explained by a reduced willingness to engage in this strategy, but rather is due to age-related limitations in the cognitive processes involved in MB decision-making. In line with this hypothesis are recent findings demonstrating that older adults are capable of increased MB behavior when the task demands on representing the decision-making structure are reduced (Ruel et al., 2021).

Overall, it seems that older adults may perceive the costs associated with cognitive control as much greater than younger adults do during cost–benefit trade-offs, and thus refrain from cognitive control to a greater degree. When sufficiently incentivized, older adults demonstrate increased performance on basic cognitive tasks, yet do not show greater meta-control when faced with a decision-making task. One possible explanation for these findings is that older adults fail to represent the task structure, and thus resort to a habitual strategy (Bolenz et al., 2019). Such a failure might be indicative of a "hard limit" to processing, past which no amount of reward can offset the predicted costs. In line with this point, in simpler cognitive tasks where they are sufficiently incentivized, older adults may be capable of engaging in greater cognitive control. While it is unclear if the cost of cognitive control also looms greater for children, they also demonstrate a similar effect whereby under the age of 11 or 12 years, children fail to engage in cost–benefit trade-offs. Thus, a similar mechanism as that described for the older adults may be at play in children, in which they too are incentivized to utilize simpler cognitive strategies to offset increased computational costs. Ultimately, when task demands are adjusted to complement cognitive abilities, participants in both age groups successfully engage in trade-offs and even show enhanced MB behavior in response to motivational in incentives (Ruel et al., 2021; Smid et al., 2020).

7 | RESOURCE-RATIONAL THEORIES OF META-CONTROL ACROSS THE LIFESPAN

Several theoretical models have been proposed to explain the computations by which individuals weigh the costs and benefits of engaging in control, and how motivation may influence the resulting trade-off (see Section 5). While each model captures the basic process by which individuals compute cost–benefit analyses, they fail to consider the impact of lifespan changes in cognitive limitations on the ability to engage in meta-control or explains these changes in meta-control as deficit-driven (Dixon & Christoff, 2012; Shenhav et al., 2013).

Griffiths et al. (2015), Leider and Griffiths (2017, 2020); Shenhav et al. (2017) have proposed a theory that integrates principles of the rational use of limited resources with realistic cognitive constraints. Based on foundational work by Herbert Simon (1955, 1956) who argued that rational decision strategies must be adapted to both the structure of the environment and the mind's cognitive limitations, Griffith's *resource-rational model* considers which cognitive operations are possible for individuals to complete and how costly those operations are in terms of time and available resources. In contrast to models reviewed above, the *resource-rational model* considers the cognitive resources available to the individual. These models posit that people can make (boundedly) rational decisions based on characteristics of the task, the environment, and—most importantly—the individual. Specifically, the model suggests that people aim to balance the amount of time necessary to execute a cognitive strategy with the expected reward it will yield. They do so by approximating both these values through a computationally cheap approximation mechanism, so as not to artificially increase effort costs at the meta-level (see Lieder & Griffiths, 2017). From this perspective then, engaging in the use of heuristics is not necessarily suboptimal, but may reflect a computationally justified analysis of the task's demands and benefits, as well as an individual's available resources. We argue that such a model better accounts for current empirical findings of individuals' meta-control abilities across the lifespan.

In what follows, we review two novel theoretical accounts that may jointly explain how cost–benefit analyses change across the lifespan. In line with a resource-rational approach, rather than suggesting that children and older adults are suboptimal in their meta-control, these two models hold that they are boundedly optimal decision-makers within the constraints of their limited cognitive abilities.

The first model has been proposed in the context of a study examining the performance of children, young adults, and older adults in a predictive-inference task in which participants had to continuously update their predictions based on uncertain (noisy) information. Specifically, participants had to adjust their predictions regarding the position of an invisible helicopter based on bags dropped by the helicopter that provided uncertain information about its true hidden location (Bruckner et al., 2020; Nassar et al., 2016). One major empirical finding by Bruckner et al. (2020) was that children and older adults showed strongly enhanced perseverative behavior when compared to younger adults. That is, they failed to update their predictions and this effect was particularly pronounced for small prediction errors, when the update is potentially more effortful. The authors show that perseverative behavior in children and older adults can be explained using a *satisficing model* in which children and older adults stop updating their predictions at a threshold that they are satisfied with rather than continuing to update their predictions optimally (Figure 2).

In the context of more standard choice tasks, the *satisficing model* would suggest that children and older adults may stop adjusting their behavior because they do not see the additional value, and/or because they do not have the cognitive control abilities to do so. In line with the studies reviewed above, the satisficing model predicts that children and older adults do not engage in greater cognitive control when small behavioral adjustments are needed as the costs associated with doing so does not exceed the associated benefits or if their current behavior or strategy already results in satisfactory rewards for the amount of effort they are engaging in (Bolenz et al., 2019; Decker et al., 2016). Yet, when provided with greater incentives or when task demands are reduced, leading the benefits to now outweigh the costs, both children and older adults may demonstrate greater control (Ruel et al., 2021; Smid et al., 2020). Interestingly, this hypothesis is in line with Simon's suggestion that the pressure for adaptation makes it rational for children and older adults to use a heuristic that selects the first option that is good enough instead of trying to find the ideal option (Simon, 1955, 1956). Simply put, perseveration might occur because the cognitive demands of the task exceed the individual's cognitive resources (see Gershman, 2020). Nevertheless, more research is still needed to understand if the satisficing behavior seen in children and older adult is a result of choices from parallel or sequential option consideration. While the former seems more cognitively demanding, making this option somewhat less plausible, future work should examine this proposal empirically.

Another theoretical explanation comes from recent findings examining the opportunity cost of time across the lifespan. By using paradigms in which the average reward rate per unit time fluctuates over the course of the task, these

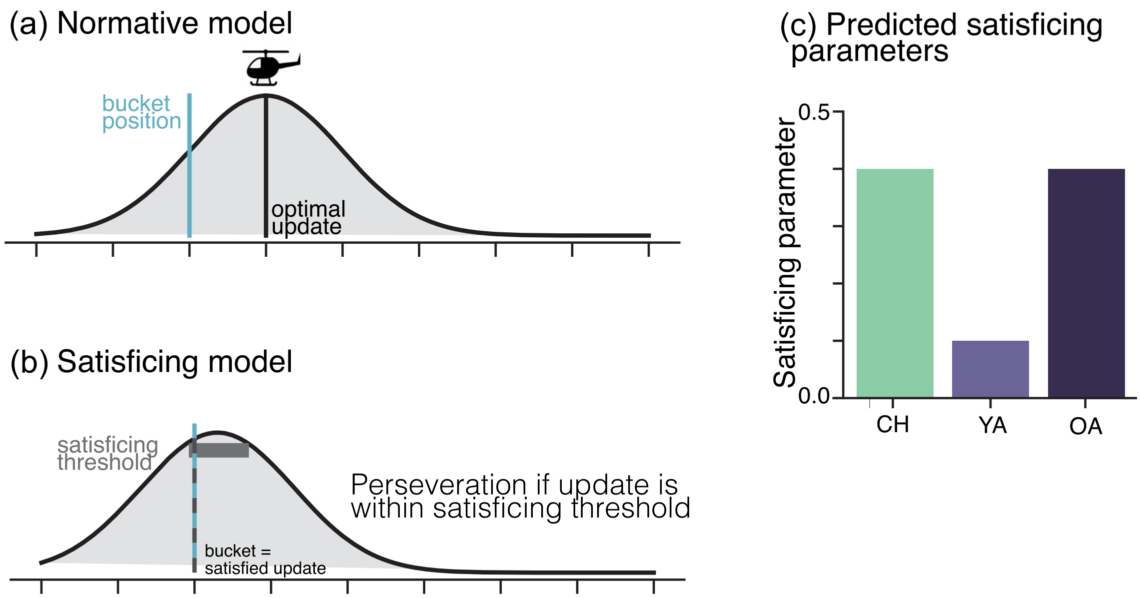

FIGURE 2 Visual representation of the satisficing model. (a) The model predicts that normative behavior (similar to younger adults) is characterized by updates of predictions to the most likely outcome (mean of the distribution / helicopter position). (b) In contrast, in line with a satisficing model, children and older adults update their predictions until reaching the satisficing threshold, at which time an acceptable position is established and they start perseverating. (c) Example satisficing criteria by age group

studies allow for the examination of participants' decisions to engage in cognitive control (i.e., meta-control) as reward rates change. This work demonstrated that while children and older adults expend cognitive effort when the opportunity cost of time is high (i.e., when the average reward that can be obtained by answering correctly per unit time is high), younger adults and adolescents withhold effort (Devine et al., 2020). The authors suggest that these differences in effort avoidance might be explained from a resource-rational perspective. Specifically, they argue that young adults and adolescents may withhold resources when rewards are abundant (i.e., opportunity costs are high), preferring instead to save their finite cognitive resources for when rewards are infrequent. Instead, children and older adults, recognizing their limitations, may prefer to invest resources when it yields maximum rewards, without considering the future depletion of resources. Extrapolating from these findings, we suggest that children and older adults may have a *sweet spot* at which the incentivization structure and the cognitive demands of the task are tailored to the needs of the different age groups (see Devine et al., , 2020). That is, based on a combination of age-related and individual cognitive limitations, we suggest that each participant will have a *sweet spot* at which they will demonstrate optimal engagement in meta-control. Critically, this sweet spot will reflect individuals' age-related cognitive limitations, while also maintaining that their decisions are rational and optimal given the boundaries of the task, the environment, and their cognitive abilities (Figure 3).

Current theoretical models on motivation and cognitive control explain the behavior seen in children and older adults as a consequence of deficits in the ability to engage in meta-control and thus interpret their behavior as sub-optimal (Dixon & Christoff, 2012; Shenhav et al., 2013). In contrast, the two models we propose suggest that children and older adults behave optimally given the internal and external constraints that they face.

Combining both the satisficing model as well as the sweet spot hypothesis may clarify how lifespan changes in cognitive control explain changes in meta-control. That is, individuals make optimal metacognitive decisions only when they are motivated to and have the available resources to do so (*sweet spot hypothesis*). Yet, when they fail on either of these criteria—to see additional value in effort investment for the relative computational costs the system must engage in—they will disengage from control (*satisficing model*). In this sense, we can see how the satisficing and sweet spot models both reflect the core tenet of a resource-rational approach: namely that they consider optimal decision-making to be the best possible use of one's limited cognitive resources. From this perspective, children's and older adults' use of simpler, less effortful, heuristics need not be the result of capacity limitations or poor reasoning per se, but can be thought to be the product of an optimal resource rational decision-making process. Combining these models under a

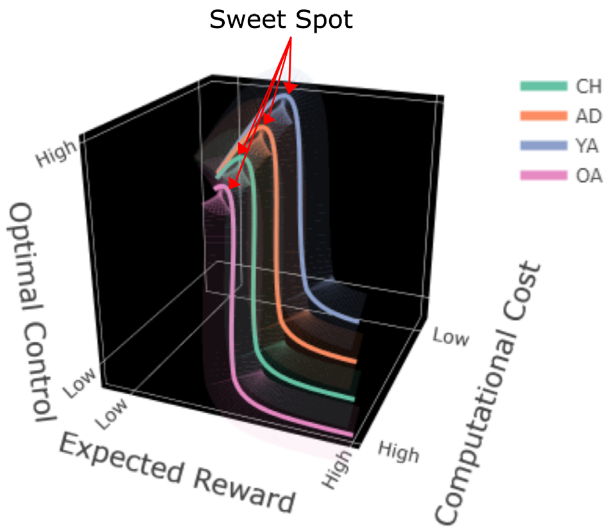

FIGURE 3 Graphical representation of the sweet spot hypothesis. The *y*-axis represents the expected reward from engaging in control, which is fixed and stable across age groups. The *x*-axis represents the computational costs of applying said strategy, which is exaggerated for older adults and children who have capacity limitations. The *z*-axis represents the degree of optimal control one ought to invest given the relative benefits and costs of engaging in cognitive control. The colored curves represent the points at which these three axes intersect for each age group. Shaded areas around each line represent individual variability within each age group. As can be seen from the figure, as computational costs increase, but reward remains stable across age groups, the optimal level of control decreases. Thus, the peak of each curve represents the "sweet spot" in which the relative cost–benefit structure yields optimal cognitive investment. Notice also, however, that these peaks remain lower for children and older adults, reflecting their reduced cognitive capacities

resource-rational framework therefore highlights the idea that children and older adults are not suboptimal decision makers. Instead, their decisions are at least as rational as young adults' decisions with respect to their abilities.

8 | CONCLUSION

In conclusion, we argue that humans are resource-rational decision makers. We paint an optimistic picture of decision-making across the lifespan not as a process defined by peaks and valleys of successful or failed decisions, but as one of adaptation to a changing world. In this sense, our proposal joins other theories of lifespan development in thinking of human aging as a process of growth and increased agency, wherein people make adaptive decisions to achieve their everchanging goals (Brandtstädter & Rothermund, 2002; Heckhausen et al., 2010). While life is characterized by periods of cognitive development and decline, we propose that humans' decisions are resilient to these changes and always seek to do the best with what is available.

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Alexa Ruel: Conceptualization; resources; visualization; writing-original draft; writing-review and editing. **Sean Devine:** Visualization; writing-review and editing. **Benjamin Eppinger:** Conceptualization; funding acquisition; resources; visualization; writing-original draft; writing-review and editing.

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