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A Rational Account of Cognitive Control Development in Childhood

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Abstract

Cognitive control is defined as a set of processes required for the organization of goal-directed thoughts and actions. It is linked to success throughout life including health, wealth, and social capital. How to support the development of cognitive control is therefore an intensively discussed topic. Progress in understanding how this critical life skill can be optimally scaffolded in long-lasting ways has been disappointing. I argue that this effort has been hampered by the predominant perspective that cognitive control is a competence or ability, the development of which is driven by predetermined maturational sequences. I propose that this traditional view needs to be overhauled in light of a growing body of evidence suggesting that cognitive control allocation is a both highly dynamic and rational process subject to cost–benefit analyses from early in development. I discuss the ramifications of shifting our perspective on cognitive control mechanisms in relation to how we design interventions. I close by spelling out new avenues for scientific inquiry.

Contents

INTRODUCTION

What Do We Mean by Cognitive Control?

Cognitive control encompasses a set of processes enabling us to pursue and attain long-term goals while responding flexibly and adaptively to changes in the environment. Imagine you have been invited to prepare an 8,000-word review article on a topic you are flatteringly considered to be an expert on. Succeeding at submitting a piece of work on time that one might even be proud of will require a number of things: (*a*) focusing on and maintaining the goal of writing a comprehensive piece of work by a deadline, (*b*) inhibiting the desire to give in to a plethora of distractions and temptations that might keep you from achieving this (e.g., subscriptions to multiple streaming services), and (*c*) shifting or adapting such goal pursuit in response to changing priorities (e.g., feeding one's hungry children, responding to an earthquake). The term cognitive control is frequently used interchangeably with terms such as executive function, self-control, or self-regulation, although each of these stem from separate research traditions and are therefore referenced and studied differently (for a helpful discussion of this, see Munakata & Michaelson 2021). Here I use the term cognitive control because the word cognitive makes explicit the set and type of processes involved (though which processes are included is still under debate; Friedman & Miyake 2017, Miyake & Friedman 2012) and the word control links this concept with frameworks in computer science and engineering, engendering ideas of optimal use (Todorov 2009), a concept central to what I propose.

Why Is Cognitive Control Important?

Research interest in cognitive control has been considerable and has continued to increase over the last two decades (**Figure 1**). This interest can be explained at least in part by the fact that cognitive control occupies a central role in everyday functioning that is core to how our thoughts and actions are organized. Cognitive control is also highly relevant clinically as its impairment seems

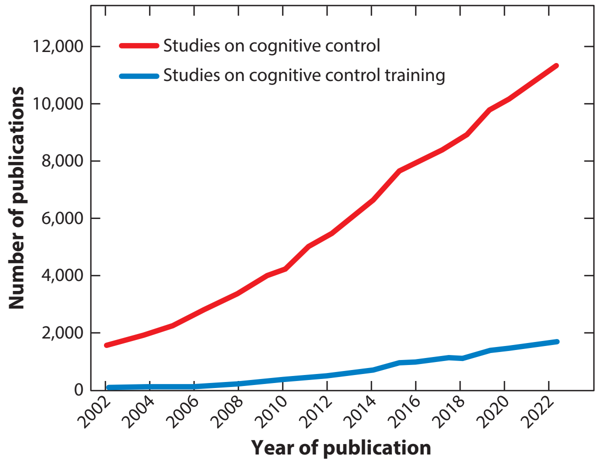

Figure 1

Publication trends for cognitive control and cognitive control training over the last 20 years. Search terms also included "executive functions," "self regulation," and "self control."

to cut across transdiagnostic boundaries in terms of posing as a risk factor for the onset of mental health problems (Caspi et al. 2014). That cognitive control is also central to predicting later life success stems from early observations using the so-called marshmallow test (Mischel et al. 1989). Here children are presented with the choice of either consuming a marshmallow that is right in front of them or holding out and getting a second marshmallow. Stark individual differences were found, with children varying in the extent to which they waited (Mischel et al. 1989). The marshmallow test has been argued to tap into cognitive control in that it requires children to keep the prospect of a second marshmallow in mind (goal maintenance or working memory) while simultaneously resisting the temptation of reaching for what is in front of them (inhibition). Interestingly, waiting was in turn underpinned by a wide array of strategies, including avoiding looking at the reward, diverting or distracting oneself, and focusing on abstract qualities of the reward (Mischel et al. 1989). Most relevant for the purpose of this review, however, was the finding that the longer children waited during the marshmallow test, the better they did academically several years later (Shoda et al. 1990). These early findings have since been buttressed, showing a predictive relationship between wait times and short- and long-term socioemotional and academic performance outcomes (Ayduk et al. 2000, Duckworth et al. 2013, Watts et al. 2018). The long-term association between waiting during the marshmallow task and other measures of cognitive control, such as performance on the go/no-go task and functional activity of the inferior frontal gyrus (see **Table 1**) (Casey et al. 2011) have led to the idea that delaying gratification might act as a stable individual difference. However, contextual factors, including perceived reliability of the experimenter (Kidd et al. 2013) as well as their trustworthiness (Michaelson & Munakata 2016), have also been shown to play an important role, in addition to group norms (Munakata et al. 2020).

Since then, there have been multiple demonstrations of a range of cognitive control measures, including tasks as well as teacher- and parent-reports, predicting current and later life success as well as educational outcomes, as assessed by math and reading scores (Robson et al. 2020). For instance, one highly cited study demonstrated a longitudinal association of children's self-control between ages 3–11 years comprised of multi-rater assessments and health, wealth, and delinquency 20 years later (Moffitt et al. 2011). Interestingly, this study also demonstrated that children who improved their self-control by adolescence (i.e., by changing rank order in the cohort) had better

Table 1 Overview of tasks used to study cognitive control development

Task	Primary construct(s) measured	Description	Correlated mechanism(s)	Age(s) tested
Stroop	Cognitive control/ interference control	In the first trial, participant must name all the colors from a list where the color named has a matching font color. In incongruent trials, the font color is different from color named.	Inhibition Attention Cognitive flexibility	Standard task has been used in children as young as 8 years; modified versions including an auditory and a pictorial version have been used for younger children
Simon	Cognitive control/ interference control	One arrow out of four (pointing to northeast, northwest, southeast, or southwest) appears in one out of the four positions on a computer screen (upper right, upper left, lower right, and lower left). Participant is required to ignore the position and to respond according to the pointing direction of the arrows by pressing the corresponding button.	Inhibition Attention Cognitive flexibility	From 5 years
AX continuous performance	Cognitive control	Participant responds by pressing a particular button when a target is presented and a different button when any other stimulus is presented. In a typical study, the target letter is X. However, X is a target only when preceded by letter A. Thus, if participant sees A-X-A-X, both Xs are targets. If participant sees B-X-B-X, neither X is a target.	Inhibition Attention Cognitive flexibility Working memory	Typically from 5 years but adapted version has successfully tested 3.5-year-old infants
Stop-signal reaction time	Inhibition	Participant responds to an arrow stimulus by selecting one of two options depending on the direction in which the arrow points. In inhibition condition, the participant must withhold making that response if an audio sound is heard.	Attention Cognitive flexibility	From 7 years, with a modified version for younger children
Go/no-go	Inhibition	Participant responds to stimuli by pressing a button when they see a go signal and inhibit when they see the no-go signal.	Attention Cognitive flexibility	From 7 years
Antisaccade	Inhibition	Participant fixates on a motionless target. A stimulus is then presented to one side of the target. Participant is asked to make a saccade in the direction away from the stimulus. Failure to inhibit reflexive saccade is an error.	Attention	From 6 years

(*Continued*)

Table 1 (*Continued*)

Task	Primary construct(s) measured	Description	Correlated mechanism(s)	Age(s) tested
Flanker	Inhibition	Participant makes directional responses to a central stimuli that is flanked by items over repeated trials, which may call for the same direction as the stimulus (congruent), the opposite direction (incongruent), or neither (neutral).	Attention Cognitive flexibility	From 3 years
Balloon analog risk	Risk-taking and inhibition	Participant can pump air into a balloon by pressing a button. Participant earns rewards for each press that inflates the balloon without popping it. Participant loses all rewards if balloon pops.	Attention	Typically used in adolescents but has been administered to children as young as 8 years
Marshmallow test	Delay of gratification	Participants (typically children) are given a marshmallow and told if they refrain from eating the marshmallow within a certain time frame, they will get two marshmallows. Child fails if marshmallow is eaten before time is up.	Inhibition Working memory	3.5–7 years
N-back	Working memory	Participant is presented with a sequence of stimuli and is asked to indicate when the current stimulus matches the one from a number of steps (*N*) earlier in the sequence. *N* is adjusted to make the task more or less difficult.	Inhibition Attention	From 7 years
Corsi	Working memory	Experimenter taps out a sequence on nine blocks, then asks participant to repeat. This is repeated several times with several different lengths of sequences.	Inhibition Attention	From 6 years
Dimensional change card sort	Cognitive flexibility	Participant is shown two cards each with a different colored object and is asked to match a third card to the correct initial card based on dimensions (object shape or color). This is repeated for several trials. In the second block, rules switch and participants are then asked to match based on a different dimension. In the final block, rules are changed constantly between trials.	Inhibition Attention Working memory	From 3 years

(*Continued*)

Table 1 ***(Continued)***

Task	Primary construct(s) measured	Description	Correlated mechanism(s)	Age(s) tested
Gift task	Emotion regulation	Experimenter wraps up a disappointing gift (e.g., a block of wood) as a reward for completing other tasks. Child opens gift and their reaction to the disappointing gift is recorded and coded by the experimenter.	Inhibition	From 4 to 6 years
Tower of London/Hanoi	Planning and problem solving	Participant is presented with two boards with pegs and different colored beads on them. Participant must match one board to have the same pattern as the other, moving only one bead at a time within a restricted number of moves.	Inhibition Working memory	Typically from 7 years upward; has also been run on children as young as 5 years
Wisconsin card sorting	Abstract reasoning and cognitive flexibility	Participant is presented with different cards and asked to match them. They are not told what criteria to base matches on but are given positive or negative feedback after match has been made.	Inhibition Attention Working memory	From 6.5 years
A-not-B	Object permanence	Toy is hidden under box A within participant's (typically an infant) reach. Infant searches for toy, looks under box A, and finds toy. This is repeated several times, then, in critical trial, the experimenter moves the toy under box B, also within easy reach of the infant. An error is made if infant looks under box A when they have observed object being placed under box B.	Inhibition Cognitive flexibility	From 7 to 12 months

outcomes by the age of 32 years, suggesting that improvements, regardless of their origin, have beneficial impact years later.

Why Should We Care About Getting Cognitive Control Right?

The above shows how critical cognitive control seems to be to positive developmental outcomes and trajectories. Coupled with the fact that cognitive control is supported by neural mechanisms belonging to a cluster of late-developing brain regions (Casey 2015, Fiske & Holmboe 2019, Luna et al. 2015, Shanmugan & Satterthwaite 2016), it is no surprise then that this has stimulated a massive research undertaking seeking to improve cognitive control (**Figure 1**). The holy grail in this endeavor has been to see whether there are tangible improvements in associated functions that are critical to everyday functioning, such as mental health, intelligence, educational attainment, or social interactions (Smid et al. 2021). However, while cognitive control is easily impaired over shorter and longer periods of time, for instance by stress and quality of sleep (Husa et al. 2022, Whitney et al. 2019), it has been notoriously difficult to create lasting improvements (Sala & Gobet 2017a,b, 2019, 2020a,b). Even more so, it appears that specific cognitive control processes are malleable, yet transfer to other domains is rare and hard to replicate. In contrast, education clearly appears to be able to leverage core processes of learning (Dekker et al. 2022), such as generalization to improve other domains (e.g., IQ) (Ritchie & Tucker-Drob 2018). Why then, in spite of its crucial role in positive current and later life outcomes across a host of domains and its reliance on late-developing and presumably highly plastic brain regions, has it been so difficult to translate findings from basic research on cognitive control into applied contexts?

Why We May Have Gotten It at Least Partially Wrong

I argue that how we conceptualize, operationalize, measure, and interpret cognitive control has critical ramifications for how we seek to restore it in case of impairments or support and improve it during typical development. I make the case here that cognitive control performance has traditionally been studied as and equated with a stable capacity, ability, competence, or resource (Baumeister et al. 1998). While these models have dominated cognitive psychology and neuroscience (Heatherton & Wagner 2011, Wagner et al. 2013), they have since been revised given a lack of supporting evidence (Inzlicht & Schmeichel 2012, Inzlicht et al. 2014, Kurzban et al. 2013). Such a revision has not followed suit in developmental psychology, where the language around cognitive control performance (or failure) continues to invoke notions of (in)ability or (lack of) capacity and competence. Such a view is nurtured by neuroimaging data supposedly demonstrating fixed developmental sequences involving the supporting brain regions. Critically, the implication of a resource model of cognitive control development is that interventions should aim to improve this capacity wholesale to see tangible benefits. However, there has been a growing view that cognitive control performance is influenced by a broad range of factors. Even more so, these influences are highly systematic and reveal that cognitive control performance is governed by a rational process that includes computations of effort and likely reward. I review developmental evidence in support of this view and discuss the implications of a such a new conceptualization of cognitive control for interventions. I do not discuss nomenclature or factor structure, nor do I delve deeply into the neural processes underpinning cognitive control development. Instead, this review advances a metalevel argument on how the construal of cognitive control development requires an overhaul.

THE PREVAILING PARADIGM

This section begins by outlining the observed developmental changes in cognitive control throughout childhood, adolescence, and adulthood. This is followed by an overview of the relevant brain regions and a review of studies that have identified structural or functional changes therein to support developmental changes in cognitive control. This gives a helpful overview of canonical descriptions of developmental change as well as offers an insight into the language used to make these descriptions.

As anyone living or working closely with children will be able to report, with age, children's cognitive control visibly improves across the board. Take, for instance, game play: As children grow older, they are increasingly able to wait their turn (i.e., inhibition), remember and improvise on the rules of a game (i.e., working memory), and flexibly adjust to where playing a game is appropriate (i.e., flexibility). Such improvements have been captured well by a host of tasks as well as questionnaire measures (**Table 1**). One example of this and one of the earliest tests (both historically and ontogenetically) of cognitive control in children is the so-called A-not-B task (Piaget 1954). It entails a demonstrator repeatedly placing an object under one (A) of two opaque containers (A and B) in full view of an infant. After each hiding the infant is allowed to retrieve the object. This is followed by test trials where the demonstrator places the object under container B and allows the infant to search for it. Typically, 8–12-month-olds will search under container A, where it was previously hidden, despite having just witnessed the object being hidden under container B. This is known as a perseverative search error and is meant to demonstrate infants' inability to inhibit a previously learned response. As is clear from this example, our knowledge of cognitive control development, and any other cognitive function for that matter, is predicated entirely on designing tests that are sensitive to specific abilities within the tested age range. While this makes it difficult to capture true developmental change given that tests differ between age groups, such patterns can be triangulated across a range of tasks. Therefore, tasks assessing inhibition and other cognitive control functions (**Table 1**) become increasingly sophisticated and complex, able to tap into individual and developmental differences for a given age group. Thus, children improve at inhibiting impulses and urges (Zelazo et al. 2013), they manage to retain and manipulate more information in their working memory (Davidson et al. 2006, Diamond 2013), and they are better able to flexibly respond to changes in their environment (Davidson et al. 2006, Diamond 2013). Cognitive control develops particularly rapidly during early and middle childhood (Davidson et al. 2006, Fiske & Holmboe 2019) and continues to improve during adolescence (Ordaz et al. 2013). Indeed, several studies have found that distinct domains of cognitive control mature at different stages (Davidson et al. 2006, Xu et al. 2013). While the precise nature of these developmental trajectories also depends on the type of task and the beginning and end point of the ages tested, recent efforts with comprehensive task batteries and large samples have shown how this question is best addressed (Tervo-Clemmens et al. 2022).

In addition to such quantitative improvements in cognitive control, there are also qualitative changes during development. These include a shift from reactive to proactive control, whereby younger children recruit cognitive control more on an as-needed basis, gradually moving more toward proactive maintenance of goal-relevant information, preparing for an upcoming need to engage control (Chatham et al. 2009). Proactive engagement of cognitive control has been shown to then become increasingly efficient during childhood (Chevalier et al. 2018) and into adulthood (Chevalier et al. 2020). Such improved goal maintenance has also been argued to produce an additional qualitative shift, namely from externally driven to self-directed cognitive control (Munakata et al. 2012), as indicated by a decrease in reliance on external cues to produce goal-relevant behavior. Such endogenous cognitive control has been shown to improve during childhood (Hayre et al. 2022) and into adolescence (Kave et al. 2008).

The predominant interpretation of these changes in performance is that they reflect the development of a competence, capacity, or ability. According to this view, the reason that young children cannot inhibit, retain more information, or adopt a new behavioral rule is because they are in some way failing, being unable to do so or lacking a component of what would allow them to do so. A few examples from the literature (including from myself) that exemplify this commonly held belief include, "The ability to consistently exert cognitive control improves into adulthood as the flexible integration of component processes. . .increases" (Luna et al. 2015, p. 151), and, "Over the past decades, a wealth of results has shown that the ability to exert cognitive control increases from early childhood to late adolescence" (Crone & Steinbeis 2017, p. 205). Such a notion is further endorsed and buttressed by the presentation and discussion of neuroscientific evidence.

There is a solid evidence base that cognitive control draws on frontoparietal circuitry, which in turn underpins the development of cognitive control during childhood (Casey 2015, Fiske & Holmboe 2019, Luna et al. 2015, Shanmugan & Satterthwaite 2016). Extensive changes in frontal and parietal cortical volume and functional connectivity over development have been shown to mediate changes in cognitive control (Buss & Spencer 2018, Tamnes et al. 2010), and the development of segregated structural brain modules, particularly of frontoparietal cortex, has been shown to mediate age-related improvement in cognitive control in children and youths (Baum et al. 2017). Thus, the functional and structural maturation of this brain circuitry seems to drive the emergence of and change in cognitive control. Such biological embedding of developmental changes provides a satisfyingly mechanistic explanation of how cognitive control develops, namely as a function of the relative state of maturity of supporting neural mechanisms. Thus it has been claimed that "improved cognitive control performance with age. . .results from a process of functional maturation marked by a greater ability to recruit the executive network and suppress nonexecutive regions in response to task demands" (Satterthwaite et al. 2013, p. 16256), that "the development of network modularity may serve as a substrate for the evolution of executive capability during youth" (Baum et al. 2017, p. 1561), and that "since the discovery that patients with damage to the prefrontal cortex (PFC) show similar deficits in cognitive control as young children, the PFC model of cognitive development has been a popular description of how cognitive control emerges over time" (Crone & Steinbeis 2017, p. 205). While there is obviously considerable nuance, for instance in accounts of adolescent development (Ordaz et al. 2013), this nuance is not always clear. The last example presents precisely the kind of inverse lesion model that is tacit in many accounts of neurocognitive development of cognitive control.

So-called resource or strength models of self-control claim that cognitive control is a limited capacity resource, which will lead to failures of cognitive control when depleted (Baumeister et al. 1998, Gailliot et al. 2007). While such accounts have been influential in spawning a flurry of empirical activity, they have failed to provide a parsimonious account of cognitive control. Critically, the basic phenomenon of ego depletion, whereby self-control is weakened as a function of prior exertion and on which these accounts draw, has been difficult to replicate (Vohs et al. 2021). Further, resource accounts of cognitive control have failed to specify what this resource might be as well as the temporal dynamics of how this resource might be depleted and replenished (Kurzban et al. 2013). While a critical engagement with resource theories of cognitive control has spawned an exciting new line of scientific inquiry in the cognitive neurosciences (Griffiths et al. 2015, Shenhav et al. 2016), the study of cognitive control development continues to be haunted by the specter of resource models.

Delineating how precisely maturation of neural circuitry drives developmental change in humans is not straightforward and presents several issues worth considering in some depth. First, it has been shown that even though many cognitive functions are fully developed by late adolescence, the brain regions providing the supporting neural underpinning, such as prefrontal and temporoparietal cortices, continue to mature well beyond that point (Somerville 2016). Second, while markers of brain structure are often used, much of what is known about the neural development supporting cognitive control development comes from functional imaging studies. Patterns of developmental change vary considerably and not systematically (Crone & Steinbeis 2017), making it difficult to reliably interpret group differences or developmental change in brain function (Poldrack 2015) and also in relation to neural and cognitive maturation. Third, test-retest reliability of neural measures is underwhelming (Elliott et al. 2020) and requires large data sets (Marek et al. 2022). Finally, behavioral performance is highly variable (Waschke et al. 2021) and even more so during development (Montez et al. 2017, Thompson et al. 2021), yet most associations between brain and behavior are based on single snapshots. As such, they are poor proxies of anything that could be inferred as a competence or ability. For that, repeated tests including boundary conditions would need to be used. While there is no denying the neural change is a critical driver of psychological change, these relationships are not one-to-one and maturational states do not equate directly with how good the performance is. In the next section, I spell out an alternative to the resource account of cognitive control and present a wealth of developmental findings it is able to explain.

COGNITIVE CONTROL AS RATIONAL OPTIMISATION OF LIMITED RESOURCES

As outlined above, cognitive control is essential to succeed in our daily lives and tasks, whether preparing a meal or a grant. Introspection, as well as a large body of theoretical and empirical work, has shown that the deployment of cognitive control is costly (Kool & Botvinick 2018, Kurzban et al. 2013, Shenhav et al. 2013). For instance, the promise of rewards boosts cognitive control performance on a range of tasks (Cho et al. 2022, Engelmann et al. 2009, Padmala & Pessoa 2011, Padmanabhan et al. 2011, Parr et al. 2022, Thurm et al. 2018). Further, when given the choice between similar outcomes, we prefer the path of least resistance with lower cognitive control demands (Kool & Botvinick 2014, 2018; Kool et al. 2010, 2013). Finally, we discount cognitive effort in ways similar to physical effort (Chong et al. 2017), and the experience of cognitive control exertion is aversive (Dreisbach & Fischer 2012, Kurzban et al. 2013, Vogel et al. 2020). Thus, cognitive control bears all the hallmarks of being effortful (Kool & Botvinick 2018). It has been argued that the main reason for this stems from inherent capacity limits of controlled cognitive processing (Shiffrin & Schneider 1984), reflecting cross talk that arises from local bottlenecks, such as when tasks compete to use the same set of computational processes or representations for different aims (Shenhav et al. 2017). The subjective experience of effort is argued to carry a critical function, namely prioritizing tasks in terms of cost (i.e., difficulty) and likely reward, though it has also been argued that opportunity costs be taken into account (Kurzban et al. 2013) given the allocation of a valuable but limited resource.

The observation that cognitive effort should be expended to the extent that it is worth doing so has been formalized in several models. According to the expected value of control (EVC) model, a person decides what level of control to allocate to a given task by computing the expected payoffs and weighing these against the cost of exerting the associated levels of effort. The difference between cost and payoff constitutes the EVC (Shenhav et al. 2013). Such a cost–benefit analysis is necessary to determine not only *what types* of controlled processes are worth investing in but also *how much* control is worth investing in each based on the returns expected for a given level of control. Other models following a similar logic include theories on the value of computation (VOC) (Callaway et al. 2022, Griffiths et al. 2015, Lieder & Griffiths 2019). The VOC model states that the best algorithm should maximize the VOC, defined as the expected utility gained by engaging those computations minus the expected cost of the computational resources it will consume (as in, e.g., central processing unit cycles and memory). Specifically, mental effort should be allocated to achieve the optimal trade-off between the expected utility of its outcome and the opportunity cost of its required time. These are just two examples of a family of models applying reinforcement learning to understanding how cognitive control is allocated (Frank & Badre 2012, O'Reilly & Frank 2006, Verguts et al. 2015).

Such VOC models offer a parsimonious account of a range of cognitive control phenomena, including the boosting effects of rewards and the phenomenology of effort. Further, unlike resource theories of cognitive control (Baumeister et al. 1998, Hagger et al. 2010), they are biologically and computationally plausible. Modeling and neuroimaging suggest that dorsal anterior cingulate cortex is a key region, integrating signals relevant to EVC and signaling to downstream regions the quality and quantity of cognitive control likely to maximize the value (Shenhav et al. 2016). Recent work setting out to test empirical predictions of the EVC model used a Stroop task modulating factors of reward and efficacy and found that participants invested more cognitive control when this control was more rewarding and efficacious (Fromer et al.

2021). The above then suggests that cognitive control allocation and therefore performance on cognitive control tasks is a highly rational process that occurs on the basis of a cost–benefit analysis in relation to expended effort and prospective reward. For the remainder of this section, I review the evidence suggesting that similarly rational processes might be at work in cognitive control allocation in children. This evidence comes from studies modulating the two primary features relevant for value of control models, namely reward and effort.

The Development of Rational Decision-Making

Evidence of rational learning and inferential processing in human infants abounds. Rational refers to the integration of prior beliefs, knowledge, and biases with new evidence (Xu & Kushnir 2013). Thus, infants will imitate adult behavior only when this makes sense in relation to a given goal (Gergely et al. 2002); they learn and reason in statistical and inferential ways (Teglas et al. 2011, Xu & Kushnir 2013), rationally infer causes of failed actions (Gweon & Schulz 2011), and assume that others select goals and actions to maximize rewards relative to their incurred costs according to a naive utility calculus (Jara-Ettinger et al. 2016). Strikingly, infants also rationally infer the value of goals from the costs of actions (Liu et al. 2017), suggesting that the computational machinery for an EVC is present already very early in development. Further, it has been shown that infants apply this knowledge to their own actions and decide when and how to deploy effort (Lucca et al. 2020), whereby infants varied systematically and rationally in whether, when, and how hard they tried based on the type of social evidence and their own ongoing experience with a task. Such rational decision-making has also been shown to impact performance on a task that is seen as a staple in the study of infants' cognitive control, the A-not-B-task. In a seminal study it was shown that perseverative search errors in 10-month-old infants are in fact halved when the object is hidden without the experimenter using the communicative cues that normally accompany object hiding in this task (Topal et al. 2008). The authors suggest that this improvement results from an interpretative bias of ostensive social cues that normally help infants learn from demonstrations but that is actually misleading when objects are hidden. This finding is striking, as it is shows infants' performance on cardinal paradigms of cognitive control are to a large degree subject to a misapplication of an otherwise rational belief.

Following on from demonstrations of robust rational reasoning and learning in infants, children demonstrate considerable capacity for rational decision-making. For instance it has been shown that children revise their beliefs in a way that is consistent with Bayesian inference (Gopnik et al. 2004, Schulz & Gopnik 2004, Schulz et al. 2007), whereby even variability in children's responses on learning tasks reflect rational motives, presumably unconsciously (Bonawitz et al. 2014). Having established then that children have the computational toolkit that would allow rational decision-making, we can turn our attention to cognitive control. Some indicators of rational decision-making come from another staple of the cognitive control literature, namely the marshmallow task. For instance, it has been shown that children's delay of gratification is substantially influenced by their belief in whether their environment is reliable or not (more impulsive in unreliable environments) (Kidd et al. 2013) or by whether they are interacting with an experimenter whom they have previously seen to be trustworthy or not (more impulsive with untrustworthy experimenters) (Michaelson & Munakata 2016). Given the tight coupling between socioeconomic status (SES) and environmental reliability, this would shed light on why the well-known association of delay of gratification and later-life academic achievement would disappear after controlling for SES (Watts et al. 2018). These findings can be integrated well with a rational account of cognitive control development. I now discuss the evidence of how systematically cognitive control during childhood is subject to rational cost–benefit analyses related to rewards and effort.

How Effort and Reward Guide Cognitive Control Allocation Through Childhood

As shown above, infants are sensitive to goal values and effort (Liu et al. 2017) and are capable of processing their relative trade-off through a cost–benefit analysis (Lucca et al. 2020). The presence of these computational principles essentially provides the developmental building blocks for the likely operation of an EVC during childhood. I begin by reviewing evidence on the effects of rewards on cognitive control in children. In terms of studying the impact of reward on cognitive control, there is extensive evidence that the use of monetary as well as social incentives modulates performance on cognitive control tasks in children as young as 4 years and robustly so during childhood and into adolescence (Fischer et al. 2018, Padmanabhan et al. 2011). A recent study looking at whether 7–10-year-old children's working memory performance is impacted by making some items to be remembered more valuable (Atkinson et al. 2019) reported an effect of value across different forms of presentation (sequential and simultaneous) and load (3- and 4-item arrays) for children of all ages. Another study compared the use of more or less cognitively effortful, value-based decision-making strategies (i.e., model-based and model-free decision-making) in 5–11-year-old children (Smid et al. 2022). Contrary to previous studies reporting model-based decision-making to emerge only in adolescence (Decker et al. 2016), Smid et al. (2022) found that using a paradigm where greater cognitive effort also led to greater rewards, children as young as 5 showed signatures of cognitively effortful, goal-directed decision-making strategies. While few studies have investigated developmental change in the extent to which rewards impact cognitive control, it would appear that this is relatively comparable throughout childhood and adolescence (Padmanabhan et al. 2011).

More interesting from the perspective of EVC is the question of whether value and effort are used to inform whether and how to engage cognitive control. While the ability to monitor one's own performance appears to be present already in infants (Goupil & Kouider 2016, Goupil et al. 2016), it has been shown that 5-year-olds might struggle to use this spontaneously but can when encouraged to do so (O'Leary & Sloutsky 2017). A recent study explored the extent to which 4–5-year-old children are sensitive to cognitive costs and reward probability when making decisions (Wang & Bonawitz 2023). Using a simple counting task that required children to count two quantities, compare their magnitude, and select the larger of the two, the authors show that children decide to give up more (persist less) when the task required more cognitive control and even more so when the likelihood of a reward was low. These findings suggest that the ability to consider and evaluate the costs of cognitive control and integrate these with the likelihood of rewards is in place by 4 years of age. A study by Chevalier (2017) assessed 7–12-year-old children's explicit willingness to engage in cognitive effort by first providing them with the experience of an *N*-back task with moderate and high difficulty and then using a discounting paradigm, measuring how much reward children were willing to forego to conserve cognitive effort. Children of all ages showed a strong sensitivity to cognitive effort, as measured through pupil dilation, and they were willing to pay to conserve cognitive effort, which in turn was predicted by pupil dilation. Interestingly, this was not captured using implicit demand avoidance paradigms (Niebaum et al. 2019) based on prior work in adults (Kool et al. 2010). Here younger and older children and adults had the opportunity to choose between two decks from which they had to sort cards on the basis of two different dimensions (i.e., shape and color). Crucially, participants were exposed to several rounds of the two decks, which unbeknownst to them differed in that one deck contained 90% rule switches (high demand) while the other deck contained only 10% rule switches (low demand). Following this familiarity phase, participants could choose multiple times which deck they preferred. While adults and 11–12-year-old children showed a strong preference for the low-demand deck as well as metacognitive signals guiding this decision, 6–7-year-olds did not. This suggests that younger children were not yet able to use task-demand signals to coordinate behavior away from effort. One interpretation of these discrepant findings is that children become better at using implicit task demand signals to avoid effort, a requirement that is lessened in the context of explicit discounting paradigms. In a recent study, this hypothesis was confirmed (Ganesan & Steinbeis 2021). Using a parametric induction of cognitive effort through an attentional switch paradigm, 79 5–11-year-old children participated in a demand-avoidance paradigm as well as an explicit effort-discounting paradigm. It was found that children of all ages were sensitive to parametric modulations of cognitive effort as indicated by self-report and that, while overall children demonstrated no implicit behavioral preference for low-effort tasks, older children stated a preference for low-effort tasks and all children discounted effort. These findings strongly suggest that while children are clearly sensitive to manipulations of cognitive effort, whether and when they use this information to guide their decisions to engage in effortful tasks depends on the extent to which effortful features are made salient to them. In sum, there is clear evidence that children's cognitive control allocation is subject to the same kind of cost–benefit analyses in terms of effort and reward as that of adults.

Metacontrol—The Optimal Titration of Effort for Rewards

While the above helpfully demonstrates that, like adults, children's cognitive control performance varies systematically as a function of the rewards at stake and anticipated effort, there is of course no denying that the limitations in cognitive processing capacities are more pronounced in children. As such they ought to be even more sensitive to the optimal use of their limited cognitive resources. It has been proposed that optimizing the use of limited cognitive resources is governed by one particular process known as metacontrol. Metacontrol refers to the dynamic arbitration of a repertoire of cognitive strategies in response to contextual demands (Kool et al. 2017). This framework states that people weigh the costs of each cognitive strategy against its potential benefits in order to decide how to invest mental resources. For such metacontrol to be effective it needs to be able to take nuance into account in terms of both available reward and effort to be expended and ideally dynamically adapt in response to changes in the environment. Adults are able to dynamically shift their allocation of cognitive resources depending on the rewards available (Kool et al. 2017, 2018), and interestingly, impairment in metacontrol appears to be a transdiagnostic risk factor for mental health problems (Patzelt et al. 2019). While the developmental evidence is still sparse, one recent study might show that metacontrol is not reliably present in children aged 5–11 years (Smid et al. 2022) but that there were substantial individual differences in this age group. Equally, older adults showed reduced adaptation of how cognitive control was allocated (Bolenz et al. 2019). In a joint behavioral and fMRI study Insel et al. (2017) used a cognitive control task that was performed with low and high stakes by adolescents and adults. It was found that while adults selectively increased cognitive control during the high stakes compared with the low stakes, adolescents did not. This developmental increase in metacontrol was underpinned by functional connectivity changes in frontostriatal circuitry. A similar developmental pattern was found in the use of physical force, where adults showed a strategic increase in force to earn high versus low amounts of money compared with adolescents (Rodman et al. 2021). Thus, the optimal use of cognitive control appears to elude children, at least under testing conditions used so far.

Interim Summary

The above makes clear that the allocation of cognitive control is already a highly rational process from early in development. Whether and how children engage in cognitive effort is dependent on what is at stake, which informs both task engagement and explicit choices to engage in tasks.

The optimal titration of cognitive effort in response to changes in the environment undergoes developmental changes from childhood to adulthood. Future work should explore the mechanisms and boundary conditions of this change and include a focus on delineating the development of the computational underpinnings of how effort is assigned and integrated with rewards as reflected in the cost–benefit analysis laid out in the EVC.

WHAT ARE THE IMPLICATIONS OF A RATIONAL ACCOUNT OF COGNITIVE CONTROL DEVELOPMENT?

As argued in this review, how we define, operationalize, and test cognitive control and its development has obvious implications for how we seek to support it. To date interventions have tacitly subscribed to a resource or strength model of cognitive control, where immature cognitive control functions, which also happen to be supported by late-developing brain regions, affording greater plasticity, are targeted in terms of increasing competence or capacity. By and large this has meant that interventions have sought to either increase working memory capacity or improve inhibition or cognitive flexibility wholesale, with no regard for context, costs, or benefits. Most strikingly, but perhaps not surprisingly in spite of a vast number of attempts, such trainings do not reliably lead to changes outside the trained context (Sala & Gobet 2017b, 2019). Insofar as how knowledge can be used for application, it would seem that capacity models of cognitive control development are not fit for this purpose.

Models of EVC have spawned a rich and vibrant research agenda, including the design of interventions that take these theoretical assumptions into account, for instance, by testing the effects of rewarding effort on subsequent transfer task performance. A recent study in adults introduced an effort-contingent reward schedule in the context of a working memory task (Clay et al. 2022). Reward was coupled with mobilized cognitive effort as captured by cardiovascular measures followed by a challenging math task to see whether reward would increase preference for effort. It was found that effort-contingent reward increased preference for the exertion of cognitive effort on new tasks. Another study sought to directly compare the effects of rewarding effort with those of rewarding performance, with the explicit hypothesis that only the former should also lead to increased effort exertion and demand seeking on transfer tasks (Lin et al. 2023). A total of 846 adult participants were assigned to be rewarded during a training phase either on effort (i.e., choosing a hard task over an easy task), on performance (i.e., doing well during the trial), or equally regardless of effort or performance. It was found that participants in the rewarded-effort group chose hard trials more during the training phase than those in the other two groups. More importantly, this finding generalized to demand seeking of the training and novel tasks. These studies raise the tantalizing and entirely parsimonious possibility that rewarding effort (over performance) can lead to greater exertion of cognitive control in novel contexts. Such findings in adults provide insight into the type of interventions that also might be effective in developmental populations.

Recent models combining EVC and metareasoning have been used to speak directly to the sustained enhancement of cognitive control (Lieder et al. 2018). These models assume that humans learn to predict the EVC of alternative control specifications from features of the situation and the control signals and that the brain then selects the control specification with the highest predicted VOC. Thus, people learn by reinforcement to predict the value of alternative control signals and control signal intensities from stimulus features, and so generalization should occur based on similarity of features. While a similar approach to the role of feature similarity between training and transfer context was argued but from a Bayesian perspective (Smid et al. 2021), the proposed model was able to account for learning in several cognitive control paradigms, including people's ability to learn when and how intensely to engage controlled processing. Thinking of the application to developmental populations, the above would suggest that the reward of effort as well as a heightened awareness of environmental signals and what they indicate in terms of cognitive control demands, including the likelihood of a reward, are potentially fruitful avenues to support and increase cognitive control during development.

A recent study (Schunk et al. 2022) tried an approach known as mental contrasting with implementation intentions. This method applies a metacognitive strategy for setting and striving toward goals as well as for overcoming obstacles to achieve those goals and effectively encourages thinking explicitly about the prospect of rewards and weighing the costs associated with pursuing said rewards. Applicable to a wide range of goals, it has been shown to be effective in adults (Oettingen 2010) but has long been believed to be too taxing for children to implement. To overcome this, Schunk et al. (2022) developed a storybook illustrating the method through a character and applying it to a range of both predetermined and self-chosen goals, which were first introduced by the teacher and then discussed in the class. Instructions were scripted, and self-regulation was effectively taught over 5 weeks during normal school time. A control group continued with regular teaching. Measures of reading, math, inhibition, and attention were collected before the intervention and 1, 6, and 12–13 months after. The authors found an effect of the intervention on reading and finding careless mistakes, both of which gradually emerged over time, and compared with the control group, the median child's performance moved from the fiftieth to the seventy-fifth percentile. Further, the intervention led to improvements on lab-based tasks measuring inhibition and attention, which also emerged over time. Most strikingly, children in the treatment group were 13% more likely to go on to a more advanced secondary school track several years later. Math scores were not impacted by the intervention.

The above clearly highlights the considerable and exciting promise held by reevaluating how we conceptualize, measure, and improve cognitive control. In the final section, I spell out some research that needs to be done to capitalize on these developments.

NEW AVENUES

While it is of course uncontested that there is clear maturation of the inherent processing limits until adulthood, where perceptual and cognitive development is marked by biological constraints imposed within relevant neural circuitry (Colonnese & Phillips 2018, Kiorpes 2016), I argue that this has been overestimated for cognitive control. Developmental psychology needs to renew its efforts to delineate what about cognitive control performance is truly competence and what is motivational. I propose two ways forward.

First, a more veridical assessment of actual ability should be obtained through repeated testing. It is known that cognitive control performance is highly variable and subject to a vast array of extraneous factors, such as hunger, sleep, stress, and mood (Husa et al. 2022, Mitchell & Phillips 2007, Whitney et al. 2019). Typically, contextual factors are not taken into account in standard testing batteries. To obtain true measures of performance, multiple short bursts of measurement should take place over a compressed period of time, which would allow assessing stability as well as variability in performance, both of which are potentially of interest.

Second, as outlined in the introduction, cognitive control serves the purpose of short- and long-term goal pursuit. It has been argued elsewhere already that understanding how cognitive control develops necessitates a better understanding of how goals develop (Doebel 2020). To date, goals are instantiated primarily through primary or secondary (e.g., money, social incentive) rewards, which are standardized and used for a large age range. Money in particular is the most regularly used incentive. But while these incentives may well work for a large age range, it is unclear whether they do so to a similar extent across ages. Money for instance is a cultural artifact (Searle

ENVIRONMENTAL CONTROLLABILITY

Under a rational framework of cognitive control, contextual variables and how they impact the relationship between the degree of cognitive effort to be expended and prospective reward play a large role. One such variable is the degree of control afforded by a given environment, that is, the extent to which specific actions lead to achieving desirable or avoiding undesirable outcomes. Environments differ greatly with respect to the extent and repertoire of specific actions that afford such control (e.g., cracking a joke will be rewarded by amusing one's peers, punished by annoying one's teachers, and simply ignored at home), and humans are remarkably attuned to whether and which specific actions effect change in a given context (Moscarello & Hartley 2017). Assessments of environmental control are present from infancy (Tarabulsy et al. 1996), where parental responsiveness is argued to lay the foundations for expectations of control. Assessing the degree of control afforded by an environment becomes increasingly accurate throughout childhood and adolescence (Raab et al. 2022). A large body of work has shown that experiences of control affordances shape the degree to which cognitive control is deployed (Moscarello & Hartley 2017). Thus, the greater the opportunity for control the more proactive, exploratory, and goal-directed behavior will be, and the more cognitive control will be harnessed to achieve the goals afforded by the environment. Environmental control and how this is subjectively perceived is therefore likely a critical determinant of the degree of cognitive control exerted. A recent study with 8–25-year-old participants found that agency (i.e., free choice versus forced choice) facilitated memory accuracy for items encoded, but only in contexts for which agency carried the greatest utility (Katzman & Hartley 2020). This effect was comparable for all age groups, suggesting that environmental control may have similar effects on how this impacts cognitive control allocation, at least from middle childhood to adulthood. Further work on how environmental control impacts cognitive control across development is needed. On an empirical side note, imagine a child being put into a novel experimental context, with little experience of the type of paradigms that many adult participants are typically much more familiar with. It is not unlikely that these factors will affect performance.

1995), the value of which is presumably acquired only with experience. The likelihood that the incentives used differ across development risks an inaccurate estimation of how cognitive control might change in relation to these goals. In fact, it has been shown that money, as opposed to primary reinforcers, does not have the same effect on children compared with adults, as measured by subjective valuation, effort discounting, and impact on cognitive control (Veselic et al. 2021). This implies that we need to increase our efforts to understand the goals of specific ages and individuals and to harness that knowledge in understanding how cognitive control development unfolds (see also the sidebar titled Environmental Controllability). In essence, this is a plea to start taking development seriously, and while this would mean a departure from the quantitative frameworks of comparison across identical stimulus types toward a qualitative approach of operationalizing goals, it would also mean gaining a better understanding of what children are actually capable of.

CONCLUSIONS

In this review I advocate for an overhaul of our understanding of how cognitive control develops. I hope to have made clear that resource theories, even though considered to be an inaccurate account of cognitive control, continue to dominate how this is studied across development. The ramifications are obviously considerable as evidenced by the lack of success at translating these findings into practice in the context of effective interventions. VOC theories offer a parsimonious account of a wealth of developmental findings and a solid and empirically testable framework within which to understand cognitive control development. This does come with significant challenges. A true understanding of the development of effort and reward or value will require us to thoroughly investigate the qualitative nature of developmental change and what makes an age group or individual of an age group tick. To date, the vast majority of experimental paradigms used to study cognitive control development are borrowed from assessments in adults, and while of course they are made child-friendly, the approach is inherently adult-centric. Such an approach further entrenches a deficit-oriented interpretation of children's performance. It is worth reflecting on the discrepancy between the wealth of abilities ascribed to infants, while children are more often seen in terms of what they seem to be lacking. A rational account of cognitive control development mandates taking child development seriously at every stage of ontogeny and introducing that understanding into the design of experimental paradigms if we are to make any significant advance in translating findings into practice.

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