Toward a Rational and Mechanistic Account of Mental Effort

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Abstract

In spite of its familiar phenomenology, the mechanistic basis for mental effort remains poorly understood. Although most researchers agree that mental effort is aversive and stems from limitations in our capacity to exercise cognitive control, it is unclear what gives rise to those limitations and why they result in an experience of control as costly. The presence of these control costs also raises further questions regarding how best to allocate mental effort to minimize those costs and maximize the attendant benefits. This review explores recent advances in computational modeling and empirical research aimed at addressing these questions at the level of psychological process and neural mechanism, examining both the limitations to mental effort exertion and how we manage those limited cognitive resources. We conclude by identifying remaining challenges for theoretical accounts of mental effort as well as possible applications of the available findings to understanding the causes of and potential solutions for apparent failures to exert the mental effort required of us.

Contents

1. INTRODUCTION

> All highly abstract conceptions, unaccustomed reasons, and motives foreign to the instinctive history of the race . . . prevail, when they ever do prevail, with effort; and the normal . . . sphere of effort is thus found wherever non-instinctive motives to behavior are to rule the day. (James 1891, p. 536)

Cognitive effort is among the most familiar and intuitive fixtures of mental life. Different tasks transparently demand different levels of cognitive exertion, with success or failure depending on how hard we try. In some cases, difficulties prompt us to apply ourselves more intently. In others, we disengage, judging the demanded effort not to be worth it, or perhaps experiencing ourselves to be depleted or fatigued (Botvinick & Braver 2015, Hockey 2011, Kurzban et al. 2013, Westbrook & Braver 2015).

Given this seemingly immediate availability to introspection, mental effort is surprisingly difficult to pin down as an object of scientific study. What exactly is mental effort, from an objective rather than introspective point of view? What exactly is going on when we try harder on a cognitive task or decide that this trying is not worth it? What is being conserved when we conserve our cognitive resources, and how do we decide the manner in which those resources get allocated? And how can we identify the neural mechanisms underlying such a subjective construct? Our aim in the present article is to review some areas of recent progress in addressing these questions.

To convert mental effort into an approachable object of scientific study, a useful first step is to operationalize it not in purely subjective conative terms but instead in terms of information processing. Drawing on previous work (Bonner & Sprinkle 2002, Camerer & Hogarth 1999, Hockey 1997, Kahneman 1973), we adopt the following working definition: Effort is what mediates between (*a*) the characteristics of a target task and the subject's available information-processing capacity and (*b*) the fidelity of the information-processing operations actually performed, as reflected in task performance. The first two factors, task characteristics and capacity, determine what level of performance is attainable in principle. Effort refers to the set of intervening processes that determine what level of performance will in fact be realized; the quality of this performance is quantified through such measures as response latency and accuracy. Drawing on the familiar analogy between mental and physical effort, we can say that task characteristics and information-processing capacity are analogous to the weight of an object and the physical strength of a person trying to lift it, and that task performance is analogous to the swiftness of the lift. Effort, then, is the thing that mediates between weight and strength, on the one hand, and the actual lift outcome on the other.

In the case of mental effort, the heavy lift accomplished through effort can take a variety of forms, many of which we discuss further below: the overriding of default actions or habits (Miller & Cohen 2001), engagement in complicated mental feats such as reasoning (Kahneman 2003), working memory maintenance (Braver 2012), and switching between tasks with different kinds of demands (Monsell 2003). And the cumulative effect of such lifting can determine important life outcomes, including academic success, social competence, and ability to cope with environmental stressors (Casey et al. 2011, Duckworth et al. 2007, Mischel et al. 1989, Tangney et al. 2004).

However, these downstream effects do not immediately tell us how effort does its work. What exactly is the nature of this mediator? If physical effort regulates the engagement of muscles, what is it that cognitive effort is regulating?

A plausible answer to this question has emerged through several decades of research on performance in cognitive tasks. This work has shown that information processing falls along a continuum of automaticity (Shiffrin & Schneider 1977), with some processes (typically heavily practiced ones) able to be deployed more reflexively and with less threat of interference from other ongoing thoughts. Processes on the other end of this continuum are said to require increasing commitments of cognitive control to reconfigure information processing away from default (i.e., more automatic) settings (Botvinick & Cohen 2015, Cohen et al. 1990). The notion of effort was in fact central to the earliest characterizations of automatic and control-dependent processing, with the former described as easy and effortless, and the latter as effortful. Thus, cognitive control may be viewed as the force through which cognitive effort is exerted.

Although this point helps to firm up a definition for cognitive effort, it leaves open one more critical issue. If cognitive effort regulates the degree to which cognitive control is engaged, how is the target level of control chosen? The notion of effort implies a decision problem: How much (and what form) of control should be allocated, given current circumstances?

This set of questions provides the central focus of our present review. In particular, we explore research aimed at understanding mental effort as a domain of decision making, focusing in particular on recent approaches that identify cognitive effort as the output of reward-based choice. According to such approaches, individuals weigh the benefits of cognitive control against some inherent cost, the nature of which we discuss next. The core of this review focuses on computational cognitive approaches to understanding this cost-benefit analysis, with the aim of providing a framework for investigating associated phenomenology and underlying neural substrates. We conclude by summarizing those substrates and considering how these help explain the subjective experience of effort and how this can be quantified.

2. WHY IS CONTROL COSTLY?

Our working definition of mental effort exposes an intriguing riddle: Why should there be any mediating factor between cognitive capacity, on the one hand, and performance on the other? Why, in other words, don't people always simply perform at the highest level of which they are capable? The intuitive answer suggested by introspection is that we are constitutively reluctant to mobilize all available cognitive resources. That is, mental effort is inherently aversive or costly. In addition to accounting for its phenomenology, the idea that control is costly helps to explain why incentives are found regularly to improve cognitive performance, suggesting that individuals can increase their control allocation when higher incentives are on offer (i.e., they are not constrained by ability) but hold back from doing so, owing to the aversiveness of the effort required (Botvinick & Braver 2015). For example, participants respond faster and more accurately when expecting greater reward for naming the color of a Stroop stimulus (e.g., when the word **GREEN** is set in red type) (Krebs et al. 2010). Similar effects have been found with task demands including selective attention (Engelmann et al. 2009, Padmala & Pessoa 2011) and task switching (Aarts et al. 2010, Umemoto & Holroyd 2014). Even performance on intelligence tests, traditionally assumed to be one of the purest measures of cognitive ability, is affected by incentive levels (Duckworth et al. 2011).

Additional evidence for the presence of cognitive effort costs comes from work on the demand-selection task (DST). In the DST, participants face a recurring choice between two options, each associated with different levels of demand for cognitive effort (e.g., higher versus lower frequencies of task switching). The key finding from this set of tasks is that participants generally prefer the course of action associated with the fewest cognitive effort demands (Dunn et al. 2016, Kool et al. 2010, McGuire & Botvinick 2010). This is consistent with findings that participants demand greater rewards to engage in tasks that demand increasing inhibitory control (Dixon & Christoff 2012) or working memory maintenance (Westbrook et al. 2013). In other words, cognitive effort is experienced as carrying disutility (i.e., as something to be discounted from the expected reward), an observation that has been further substantiated by findings that cognitive effort evokes negative emotions (Dreisbach & Fischer 2015, Inzlicht et al. 2015, Spunt et al. 2012), negatively biases learning of stimulus-reward associations (Cavanagh et al. 2014), and discounts neural responses to the reward presented after a person completes an effortful task (Botvinick et al. 2009a).

These and other findings substantiate the intuition that control is registered as costly and lay the groundwork for treating control costs as a central explanatory variable in theories of control allocation. However, before examining these theories in greater depth, it is worth first considering why a function so seemingly important as cognitive control might be encoded as costly at all.

Two broad categories of explanation that are in fact closely related to one another have been offered in response to this question: intrinsic costs and opportunity costs. The first suggests that the allocation of control itself carries a cost, and thus there is a limit on how much control can be allocated at one time. On this account, the investment of control may register as mental effort to index that cost and ensure a proper evaluation of the worth of that investment. The second type of explanation follows naturally from the first: Given that the capacity for control-dependent processing is limited by its cost, allocating control to one set of processes means forgoing pursuit of others that may also have value. On this account, the duration of a control-demanding process poses an opportunity cost (Kurzban et al. 2013) that may also register as mental effort. In the sections that follow, we consider these two types of explanation.

2.1. Intrinsic Costs of Control

The notion of limited capacity of control was a defining feature in the earliest conceptualizations of controlled processing (e.g., Posner & Snyder 1975, Shiffrin & Schneider 1977). However, it begs a fundamental question that continues to vex research in this area: Why is the capacity for control so limited? Prominent theoretical accounts offer three possible explanations: limited metabolic resources in the brain, constraints on the capacity to maintain task-relevant information, and/or

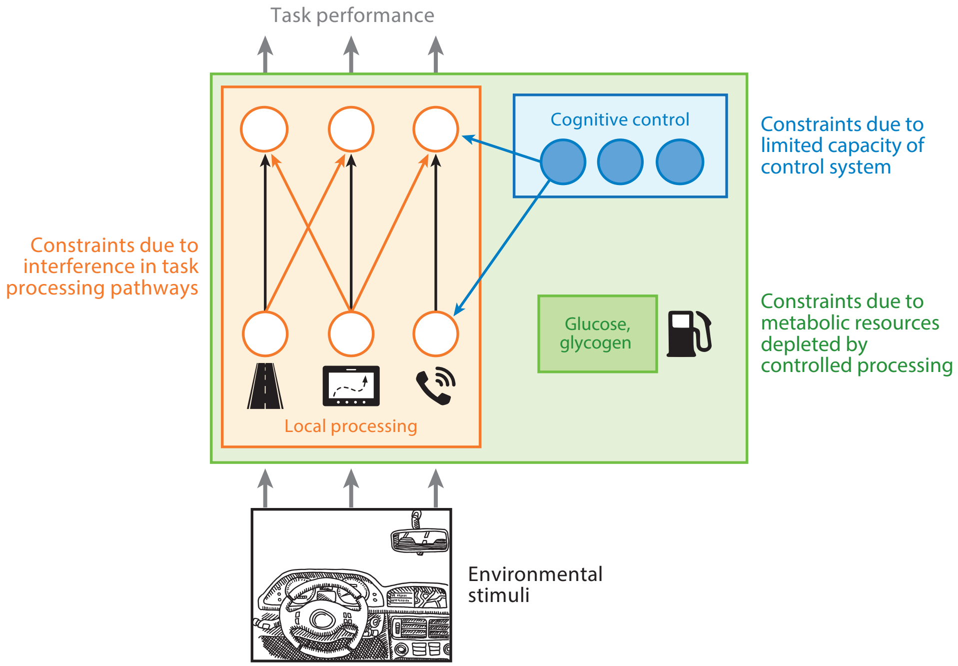

Figure 1

Schematic summary of possible control limitations. Different accounts of the potential sources of control costs are shown for an example case of a driver trying to attend multiple streams of information. Resource-based accounts (*green*) propose that control costs reflect the limitations of a central metabolic resource that depletes with extended use of cognitive control. Control capacity–based accounts (*blue*) propose that control costs reflect an upper bound on the control signals that can be deployed or control-relevant information that can be stored at any given time. Interference-based accounts (*orange*) propose that control costs reflect the risks to performance associated with the overallocation of control. These risks result from cross talk that can arise from overlap among the pathways required to process task-relevant stimuli, cross talk that it is the very purpose of control to avoid. As suggested by the visual, these accounts are not mutually exclusive of one another.

interference that arises from the use of shared representations for multiple purposes (**Figure 1**). In each of these cases, the cost of control plays a role in protecting a limited resource. What distinguishes the theories is the nature of the protected resource itself.

2.1.1. Metabolic constraints. By analogy to the exertion of physical effort, cognitive effort has been linked hypothetically to a limited physiological resource that depletes with use, much like a muscle depletes energy (or acquires toxic byproducts) as it translates contraction into force (Baumeister & Heatherton 1996, Baumeister et al. 1998, Muraven et al. 1998). According to this idea, exertion of cognitive effort is limited by a resource that depletes in proportion to the amount and duration of exertion and therefore encourages individuals to allocate their available reserves judiciously (**Figure 1**, *green*). For instance, an individual who engages in a control-demanding task over an extended period of time would find herself impaired at a subsequent task that requires control or self-regulation (e.g., choosing a healthy meal). As predicted by this resource-based account, initial evidence suggested that experimental participants indeed exert less cognitive effort on tasks that follow some amount of effort exertion (i.e., postdepletion) relative to tasks that follow minimal effort exertion (Hagger et al. 2010).

However, this account of control costs raises two questions that remain under debate. First, what is the resource being depleted? Researchers hypothesized initially that it may be blood glucose, showing for instance that participants were less depleted when administered a sweetened drink (Gailliot et al. 2007). However, subsequent experiments provided strong evidence against this hypothesis (reviewed in Kurzban et al. 2013; see, e.g., Molden et al. 2012, Vadillo et al. 2016) and suggested that, to the extent glucose improves control, it does so through an increase in motivation to perform the subsequent task rather than a replenishment of a physiological resource (Hockey 2011, Inzlicht & Schmeichel 2012). Moreover, the brain's glucose utilization is weighted heavily toward processes that do not deplete in this manner (e.g., vision), and the marginal increase in consumption for control-demanding tasks—at least some of which seem far less computationally demanding (such as two-digit arithmetic versus recognizing a face)—is estimated to be relatively small (Kurzban et al. 2013).

Some have suggested that these concerns about glucose can be avoided by alternate resource mobilization accounts that are more sensitive to controlled processing, focusing for instance on an individual's efforts to maximize astrocytic glycogen (a stored form of glucose) (Christie & Schrater 2015) or to minimize buildup of the neurotoxin amyloid-β in the interstitial fluid (Holroyd 2015), but these proposals have yet to be tested empirically. All these accounts must also address a second open question pertaining to the timescale over which putative resources deplete. Classic findings have suggested depletion of cognitive control occurs over relatively short periods of time (i.e., following less than an hour of mental effort exertion). However, recent meta-analyses and replication attempts have called such findings into question (Carter et al. 2015, Hagger & Chatzisarantis 2016). Collectively, these suggest that, to the extent control depletes or fatigues, it may do so only over longer timescales (Blain et al. 2016). We return to potential sources of these longer-timescale control costs (e.g., boredom) below but for now simply reiterate that the resource mobilization accounts suggest that these costs are operative at shorter timescales as well (e.g., individual trials of a task).

2.1.2. Structural capacity: Limitations on storage and maintenance. A second line of resource-based control cost accounts suggests that control costs may arise from computational limitations in the capacity for controlled processing rather than the depletion of any kind of metabolic resource.

The traditional, and still dominant, account explains this by making two key assumptions: (*a*) Control relies on a centralized mechanism, and (*b*) as suggested above, the capacity of this system is limited. These assumptions are typically justified by arguing that control is dependent on working memory to represent the context information (e.g., instructions, intentions, task conditions, goals) used by the control system to guide behavior (e.g., Anderson 1983, Cohen et al. 1990). This, in turn, links the constraints on control to the well-known limitations of working memory capacity (e.g., Cowan 2012, Luck & Vogel 1997, Miller 1956) (**Figure 1**, *blue*). Thus, the capacity limitations of cognitive control can be traced to the factors that limit working memory capacity, of which several have been proposed: a resource limitation in actively maintained working memory representations, in terms of discrete slots (Cowan et al. 2012, Luck & Vogel 1997) or continuous resources (Ma et al. 2014); interference between the representations held in working memory (Nairne 1990, Oberauer & Kliegl 2006); and/or passive decay (Jensen 1988, Page & Norris 1998) (for a comparative review of these accounts, see Oberauer et al. 2016).

However, these explanations have yet to be justified adequately in terms of the underlying mechanisms (e.g., the neural mechanisms involved), and, where this has been attempted (e.g., Elmore et al. 2011, Ma et al. 2014), the focus has been on simple forms of short-term memory (e.g., visual memory) and not on systems more directly involved in cognitive control. More generally, it seems odd to imagine that the control system—one so critical to adaptive behavior and with access to such vast resources (there are billions of neurons in the human prefrontal cortex alone)—would be subject to such a stultifying limitation: the inability, in many instances, to carry out more than a single control-dependent task at a time. Evolution and development would have to be rather poor engineers indeed to arrive at this solution, if structural resources available to the control mechanism(s) were the only consideration involved. (For a normative consideration of the constraints on working memory itself, see Elman 1993, Todd et al. 2009.)

2.1.3. Representational capacity: Limitations arising from information-processing pathways. An alternative to an account attributing capacity limits to the control system itself was suggested by early attention theorists and referred to as the multiple resources hypothesis (Navon & Gopher 1979; see also Allport 1980, Allport et al. 1972, Logan 1985, Wickens 1984). This proposed that restrictions in control-dependent behavior reflect cross talk arising from local bottlenecks in processing, when different tasks compete to use the same set of representations or apparatus for different purposes. As a trivial example, even with limitless capability for control, it would be impossible to say the words green and red at the same time because we have only one set of vocal chords, one mouth. However, the constraints need not arise only in effector systems (e.g., there may be only a single phonological system that drives multitasking constraints on speech), and the constraints on these effectors clearly cannot explain more common examples of multitasking failures, such as our inability to carry out two mental arithmetic problems at the same time (see Shaffer 1975 for a more interesting example and classic experimental demonstration of the problem posed by cross talk involving internal representations). From this perspective, restrictions on control-dependent processing reflect the very purpose of control—to limit the deleterious effects of cross talk in the processing system over which control presides (**Figure 1**, *orange*)—rather than an intrinsic limitation of the control system itself.

This account of capacity constraints in control-dependent processing—in terms of representation and computational properties of the processing system, rather than structural properties of the control system—gives rise to another pair of questions, both of which have been addressed by recent computational work. The first question is whether collisions in processing that give rise to cross talk are really a serious problem in a system as large as the brain. Simulation studies (Feng et al. 2014), followed by recent analytic work (Musslick et al. 2016a), indicate that even modest amounts of overlap among processing pathways can impose dramatic and nearly scale-invariant constraints on how many processes can be executed at one time. Such constraints on parallel processing have been shown to hold even in cases in which multitasking is executed as rapid sequential switches rather than as performance that is strictly parallel (Musslick et al. 2016b), under the assumption that sequential tasks bleed into one another (referred to as task set inertia) (Allport & Wylie 1999, Allport et al. 1994). Thus, it is at least plausible that even in a very large network, pathway overlap (i.e., the shared use of representations by different processes) quickly produces bottlenecks that demand management by the intervention of a control system, and that these local bottlenecks, rather than the constraints on a centralized control mechanism, may explain limits in the capacity for controlled processing. In other words, our limited capacity for controlled processing may reflect the purpose of control rather than a constraint on its ability to operate.

The deleterious impact of pathway overlap on processing raises a second question: If the bottlenecks they create are so problematic, why not avert this problem by diminishing the shared use of representations? Insight gained from the study of learning and representation in neural networks provides a direct answer to this question: Shared representation supports inference and generalization and is critical to the discovery and use of abstract structure. This insight drove the connectionist revolution in psychology in the 1980s (Rumelhart & McClelland 1986) and is driving the current explosion of interest in deep learning networks within the machine learning community (Bengio et al. 2013, Caruana 1998, LeCun et al. 2015).

Thus, the use of shared representation imposes a trade-off between its value for learning and abstraction on one hand and the constraints it imposes on the simultaneous execution of multiple processes on the other. Musslick et al. (2016b) have explored this trade-off directly. They have shown that when networks are trained to perform a variety of tasks, there is a strong bias toward the emergence of representations that are shared across tasks with similar requirements, and for control representations to develop that disambiguate the shared representations appropriately, according to task context. Furthermore, this bias considerably facilitates learning in large task spaces. However, this comes at the cost of severely degraded performance if any of the tasks involved must be performed concurrently. Additional training can overcome this limitation by separating the representations for the different tasks, which also diminishes their reliance on control (Garner 2015). These observations concur with a vast, longstanding cognitive psychological literature on the trajectory from controlled to automatic processing during skill acquisition (Cohen et al. 1990, Graybiel 2008, Shiffrin & Schneider 1977).

Musslick et al. (2016b) describe their observations in terms of a fundamental continuum of computational architectures, with those at one end that make use of independent (sometimes referred to as embarrassing) parallelism to support concurrent multitasking and architectures at the other end that exploit shared representations to support interactive parallelism in the service of abstract inference and efficient learning. From the perspective of such a continuum, the capacity constraints in controlled processing reflect the brain's choice—in those situations that demand rapid learning, the flexibility afforded by abstract inference and generalization, or both—to exploit the value of shared representation, at the cost of limits on concurrent task execution. As suggested above, mental effort can then be viewed as an explicit indicator (computational and subjective) of this cost—that is, the cost associated with situations involving processing configurations that demand the engagement of control to avert cross talk.

2.2. Opportunity Costs of Control

Although understanding the source of the constraints on controlled-processing remains an important priority for research, the constraint itself suffices to impose a closely related cost: that of time. Engaging the control system in the service of one control-demanding task means forgoing others that could have been performed over that same period. Thus, in addition to indexing the degree of investment in control itself, mental effort may also reflect the opportunity costs of that investment, as a way of ensuring that it is respected when making decisions about how to allocate control (Kurzban et al. 2013).

The idea that mental effort reflects the opportunity costs associated with allocating a valuable but limited resource—the capacity for control—is intuitively appealing. It also suggests that the perceived effort may scale with the duration of the investment. This idea accords well with work on how people assess the value (and cost) of computation and how this influences their decisions about strategies to pursue in problem solving and other behaviors—a line of work that has an intimate relationship to the cost of control. We discuss this in detail in the section that follows.

3. HOW SHOULD WE ALLOCATE COGNITIVE EFFORT?

As discussed above, the brain's inherent capacity limitations—irrespective of their cause—provide a basis for understanding mental effort costs: If a resource is valuable but limited, it should be conserved whenever possible so that it can be used judiciously. That is, cognitive effort should be expended to the extent it is worth it. This idea is central to a decades-old literature on theories

BOUNDED RATIONALITY AND BOUNDED OPTIMALITY

People's judgments and decisions systematically violate the normative principles of logic, probability theory, and expected utility theory (Tversky & Kahneman 1974). Theories of bounded rationality (Gigerenzer 2008; Simon 1956, 1982; Todd & Gigerenzer 2012) attribute these suboptimalities to people's reliance on simplifying heuristics in lieu of more exhaustive deliberation. These theories argued that such cognitive frugality reflects people's mental limitations as well as their limited time and information.

Whereas early psychological theories of bounded rationality were largely qualitative, research in artificial intelligence subsequently developed a mathematically precise, normative theory of how bounded agents should allocate their computational resources. According to the theory of bounded optimality (Russell & Subramanian 1995), the objective of rational information processing is to maximize the agent's expected reward per unit time over the long term, subject to the constraints of the agent's performance-limited hardware.

The notion of bounded optimality has inspired computational models of human cognition, according to which the brain makes optimal use of its finite resources (Gershman et al. 2015, Griffiths et al. 2015, Lewis et al. 2014). From this perspective, limitations in the brain's capacity for parallel processing (Feng et al. 2014, Musslick et al. 2016a) and its finite information-processing speed give rise to opportunity costs for each cognitive operation: Committing to one or a set of computations precludes the simultaneous execution of other valuable ones (cf. Kurzban et al. 2013). As a result, people have to trade off the expected quality of their chosen computations against the number of decisions that can be made per unit time, and in many cases the optimal amount of deliberation for each individual decision is surprisingly low (Vul et al. 2014). The limited effort that people invest in certain decisions and judgments may reflect this optimality principle (Lieder et al. 2012; Vul et al. 2014; F. Lieder, T.L. Griffiths, Q.J.M. Huys & N.D. Goodman, submitted manuscript; but see also Oud et al. 2016).

of bounded rationality, which emphasize that human cognition has to make do with limited information, little time, and bounded cognitive resources, and has been further developed into theories of bounded optimality, which specify the optimal way to use these limited resources (see the sidebar titled Bounded Rationality and Bounded Optimality).

Recent accounts have built upon this theoretical grounding to propose several ways in which complex cognitive processes can be selected so as to maximize rewards while minimizing the costs associated with mental effort. In this section, we focus on two complementary optimization approaches that have been developed in parallel within research on strategy and algorithm selection and within research on cognitive control.

3.1. The Value of Computation

To achieve bounded optimality, people may perform a cost-benefit analysis to select the cognitive strategy with the best trade-off between effort and accuracy (Beach & Mitchell 1978, Payne et al. 1988). Research in artificial intelligence has provided a mathematically precise definition of what constitutes this optimal trade-off for a given set of computer algorithms (i.e., sequences of computations) (Russell & Wefald 1991). In brief, the best algorithm should maximize the value of computation (VOC), which is defined as the expected utility gained by engaging those computations minus the expected cost of the computational resources it will consume (e.g., CPU cycles and memory). Such methods for deciding how to allocate computational resources (termed rational metareasoning) have been developed to enable intelligent systems to interact with their environment in real time to make optimal use of their limited time and finite computational resources by selecting their computations adaptively (Hay et al. 2012).

Lieder and colleagues have recently applied this optimality principle to cognition, proposing that individuals might similarly select cognitive mechanisms (e.g., decision strategies) based on their relative VOC (Griffiths et al. 2015; Lieder & Griffiths 2015; Lieder et al. 2012, 2014). Under this formulation, people should rationally trade off the quality of a selected cognitive strategy against the cost of the computations it entails (Lieder et al. 2014). Specifically, mental effort should be allocated to achieve the optimal trade-off between the expected utility of its outcome and the opportunity cost of the required time. This simple principle can account for the adaptive flexibility with which people switch between different cognitive mechanisms depending on the problem to be solved (F. Lieder & T.L. Griffiths, submitted manuscript).

These researchers have proposed that people learn to select cognitive mechanisms in a way that approximates rational metareasoning efficiently (Lieder & Griffiths 2015, Lieder et al. 2014); that is, they learn to predict the VOC of candidate cognitive operations from features of the problem to be solved and select the sequence of operations with the highest predicted VOC (see **Figure 2*a***). Such a feature-based learning mechanism can account for adaptive changes in strategy selection across a broad array of task domains, including decision making, problem solving, and mental arithmetic (Lieder & Griffiths 2015; F. Lieder & T.L. Griffiths, submitted manuscript). For example, this account was able to predict people's adaptive choices of sorting strategy when faced with an out-of-order list much more accurately than previous models of strategy selection (**Figure 2*b***) (Lieder et al. 2014). Overall, these findings suggest that when selecting between sequences of cognitive operations, people invest mental effort rationally with respect to their mental model of the (time) costs and rewards for potential strategies.

3.2. The Expected Value of Control

The VOC model describes how individuals select between sets of sequential operations based on the expected reward as well as the costs associated with the time required. However, as noted above, cognitive control is generally conceived as falling along a continuum; one can apply varying degrees of control (e.g., attention) to the task at hand, with concomitant changes in performance. Moreover, people experience higher levels or intensities of control exertion as more costly or aversive, independently of the associated time costs (Dixon & Christoff 2012, Kool et al. 2010, Westbrook et al. 2013). Thus, 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. Inspired by reinforcement learning (RL) models of action selection and motor control (Sutton & Barto 1998, Wolpert & Landy 2012), Shenhav and colleagues (2013) recently developed a theory that formalizes this idea of a cost-benefit analysis for maximizing the expected value of control (EVC).

The EVC theory proposes that control signals are specified along two dimensions: an identity (e.g., what to attend, such as the color of a Stroop stimulus) and an intensity (e.g., how strongly to attend, relative to a default or automatic level). Adjusting the intensities of control signals should influence the likelihood of obtaining reward, avoiding punishment, or both (e.g., based on providing a correct versus erroneous response), as well as the efficiency of doing so (e.g., how long it takes to respond). Collectively, these factors define the overall rate of reward receipt (reward per unit time), which is a key variable animals seek to maximize (Bogacz et al. 2006, Niv et al. 2007). In addition to discounting the value of control by the time spent on the task, the theory importantly also assumes an intrinsic cost or disutility associated with increasing control intensity. The EVC is defined as the difference between the expected gains (e.g., reward rate) and the expected control cost associated with a given configuration of control signals (**Figure 2*c***). Optimal control allocation can be achieved by selecting the control signal configuration that

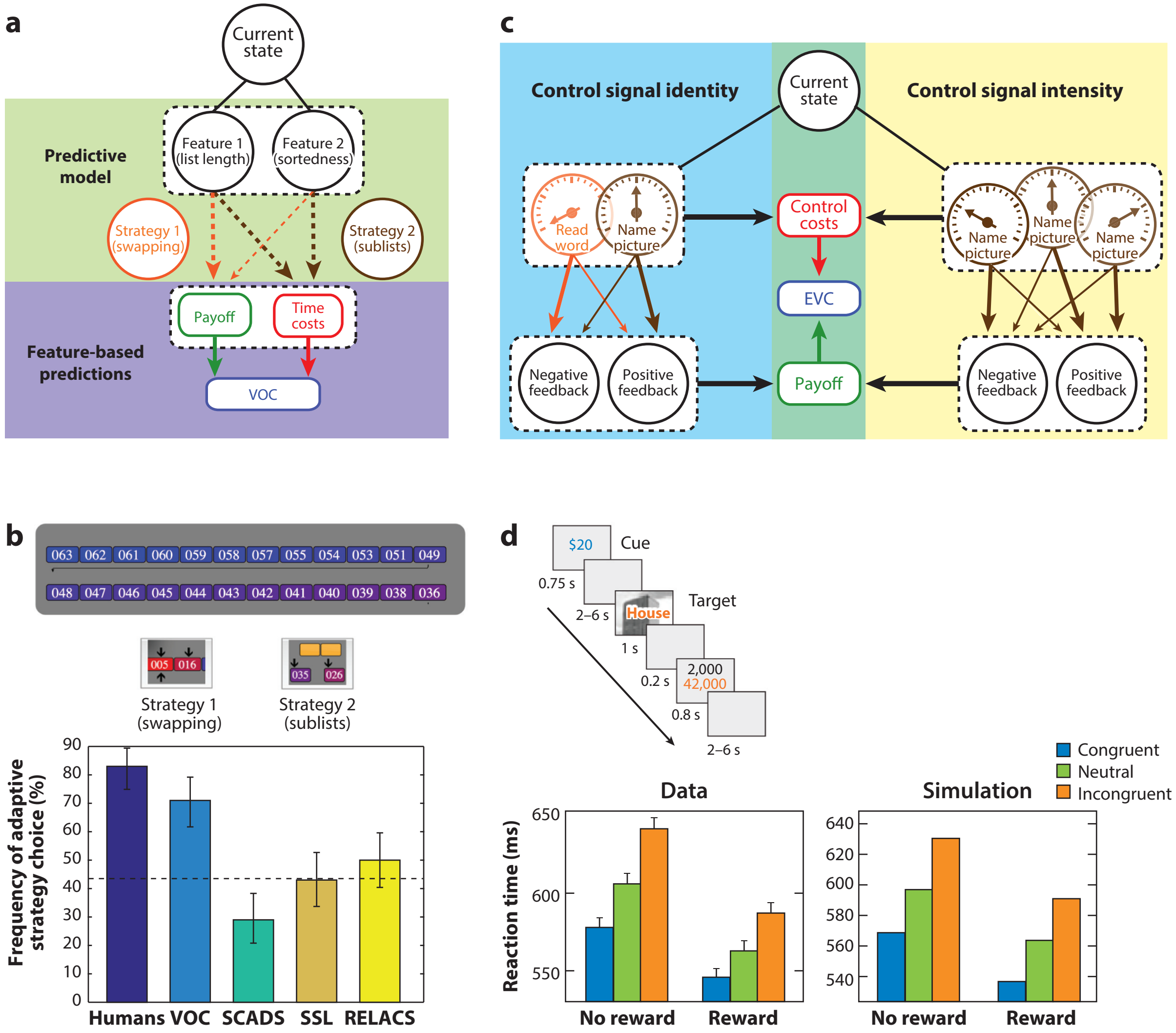

Figure 2

(*a*) The value of computation (VOC) model learns how features of the environment (e.g., the length and sortedness of a list of numbers) predict the effectiveness and efficiency of candidate computations (e.g., strategies for sorting that list), based on their expected reward and time cost (the difference between which determines their VOC). (*b*) The VOC model performed substantially better at predicting actual choices of sorting strategy than previous models of strategy selection [named Strategy Choice And Discovery Simulation (SCADS), Strategy Selection Learning (SSL), and Reinforcement Learning Among Cognitive Strategies (RELACS)]. Adapted from Lieder et al. (2014). (*c*) According to the expected value of control (EVC) theory, a given cognitive control signal setting (consisting of both its identity and intensity) determines the expected payoffs and costs for control. The optimal control signal settings maximize the difference between these two quantities, or the EVC. Adapted with permission from Shenhav et al. (2013). (*d*) EVC model simulations capture the improvements in behavioral performance (higher accuracy and faster responses) observed when varying the incentives for a picture-word Stroop task [Padmala & Pessoa 2011 (*left*), Musslick et al. 2015 (*right*)]. Participants performing this task were instructed to indicate whether the image displayed a building or house while ignoring the content of the overlaid text. Adapted with permission from Padmala & Pessoa (2011) and Musslick et al. (2015).

maximizes EVC in the current situation. Recently, a computational implementation of the EVC theory has been shown to account for a variety of phenomena associated with the allocation of control (Musslick et al. 2015), including sequential adaptation effects such as post-error slowing and incentive-driven improvement in performance on inhibitory control tasks (**Figure 2*d***).

EVC is one of a family of recent theories that have applied RL approaches to the allocation of control (Frank & Badre 2012, Holroyd & McClure 2015, O'Reilly & Frank 2006, Todd et al. 2009, Verguts et al. 2015). For instance, one recent model uses temporal difference learning to estimate the value and effort costs of both cognitive and motor actions (Verguts et al. 2015) and combines the two estimates to determine whether or not to increase the gain (signal-to-noise ratio) of either form of action selection. Building on a hierarchical extension of RL (HRL)—whereby an agent can learn the value of individual actions as well as temporally extended sequences (Botvinick et al. 2009b)—Holroyd and colleagues (Holroyd & McClure 2015, Holroyd & Yeung 2012) have proposed another model, according to which control may be used to mitigate the short-term cost of physically effortful obstacles in favor of longer-term rewards that will be obtained after completing the current sequence of actions. In other words, the HRL model selects high-level actions (called options) to maximize long-term value (e.g., walk across campus to meet a friend), and control protects those options from being delayed or overturned in the face of effortful obstacles along the way. Other models have addressed the control of behavior by using RL as the basis for selecting the information that is allowed (gated) into working memory (Alexander & Brown 2015, Frank & Badre 2012, O'Reilly & Frank 2006, Todd et al. 2009), enabling the maintenance of appropriate higher-level goals and the associated mobilization of control mechanisms given feedback from the environment.

These accounts draw upon similar basic principles of learning and action selection and are therefore potentially complementary, addressing different component mechanisms, levels of mechanistic detail, or both. A distinctive element of the EVC theory is its focus on the cost of control as a factor in the selection process. This allows the EVC theory to not only make contact with broader research into rational metareasoning and its historical predecessors but also to make detailed contact with the large, but heretofore rather qualitative, literature linking effort with incentive motivation (reviewed in Botvinick & Braver 2015).

3.3. Value of Computation and Expected Value of Control

In addition to differently emphasizing different kinds of control costs (i.e., those that scale with time alone or in addition to those that scale with level of control engagement), the VOC and EVC frameworks also maximize the value of different kinds of potential outputs. The VOC framework, with its origins in the artificial intelligence literature, frames the central cost-benefit analysis underlying effort in terms of computation. The EVC framework, in contrast, frames it in terms of cognitive control. This may appear to be a discrepancy between the two theories. However, an alignment can be established by considering the amount of computation required for controlled versus automatic processing. In comparison with automatic processing, controlled processing requires a richer representation of task or temporal context. Automatic processing, by definition, yields default behaviors; to override these, the processing system must instantiate a representation of context (such as, for example, a representation of recently received verbal instructions). Setting up this representation and deriving appropriate actions from it requires computation, and still more computation is required if the appropriate context representation must be discovered through search or deliberation. This highlights that the representational cost of cognitive control is closely related to the cost of computation. Recent research by Ortega & Braun (2011, 2013) formalizes this point, relating it to the larger theme of bounded rationality.

4. WHAT ARE THE NEURAL MECHANISMS FOR TRACKING CONTROL COSTS AND ALLOCATING CONTROL?

The theoretical perspectives we have reviewed above provide a formally rigorous framework for examining the neural substrates underlying mental effort allocation. These theories suggest that neural circuits mediating control allocation should be sensitive to the possible ways control could be allocated at a given time and the potential rewards gained (or punishment avoided) by engaging control, as well as the costs incurred by the requisite control. Furthermore, inactivating these circuits should result in motivational deficits (i.e., impaired effort allocation). These predictions have been largely borne out by research into the circuitry for cognitive control and in particular the role of the dorsal anterior cingulate cortex (dACC) within that circuit.

4.1. Effort and the Executive Network

A broad network of cortical structures has been implicated in tasks that require an individual to exert cognitive effort (Dosenbach et al. 2008, Duncan 2010, Power & Petersen 2013, Shenhav et al. 2013). This includes dACC, anterior insula (AI), lateral prefrontal cortex (lPFC), and lateral parietal cortex. The regions in this control-related network are more engaged when an individual must perform a task that demands sustained attention, maintenance of information in working memory, and/or overriding of prepotent responses; they are relatively disengaged when performing more habitual and/or externally guided behaviors. However, although the involvement of this network in research on cognitive control is robust, the functional roles of the constituents of this circuit are heavily debated, particularly with respect to potential roles in decisions about the allocation of control, as contrasted with the execution of control. Given the particular relevance of dACC, AI, and lPFC to this question, and the question of control cost signaling, we review relevant findings concerning these cortical structures and their interactions with subcortical structures and neuromodulatory systems.

Researchers have long viewed dACC (and, in particular, anterior midcingulate cortex) (Shackman et al. 2011, Vogt 2016) as playing a role in determining how physical actions, cognitive actions, or both are deployed or altered based on available evaluative signals. Early views from the cognitive control literature suggested that dACC may effect these changes by capitalizing on signals that an error had been committed (Holroyd & Coles 2002), signals of conflict between potential responses (Botvinick et al. 2001), and/or internal estimates of the likelihood of committing an error in a given context (Brown & Braver 2005). Consistent with these suggestions, dACC has been shown to signal each of these quantities (Ridderinkhof et al. 2004; Shackman et al. 2011; Shenhav et al. 2013, 2016; but see Nieuwenhuis et al. 2007) as well as other potential indicators of control demands such as surprise (Cavanagh & Frank 2014, Wessel et al. 2012). However, patterns of activity in dACC and between this region and others suggest a broader and more nuanced role than one that simply indicates how much control might be demanded at a particular point in time (Heilbronner & Hayden 2016, Shenhav et al. 2016). These patterns suggest roles in effort avoidance (Walton et al. 2007), reward-based decision making (Rushworth et al. 2004, 2011), and motivation (Holroyd & Yeung 2012, Stuss 2011), in addition to or instead of potential roles in signaling cognitive demands. The apparent involvement of dACC in these different functions can be readily explained through the lens of the control allocation models described in the previous sections.

4.2. An Expected Value of Control Perspective on Dorsal Anterior Cingulate Cortex

It has been proposed that dACC integrates signals relevant to the EVC and specifies to downstream regions the types and intensities of control that would maximize this quantity (Shenhav et al. 2013, 2016). As suggested above, this monitoring and decision-making process is informed by signals that indicate the likelihood of a certain outcome (e.g., a correct response) given a particular allocation of control, the time required to obtain that outcome, and the reward or punishment associated with that outcome. This accounts for dACC's association with indicators of cognitive demand mentioned above (e.g., errors, conflict, surprise), which can serve as proxies for performance costs (time and error likelihood). It also accounts for findings of dACC signals indicating the values of potential outcomes (Heilbronner & Hayden 2016, Kaping et al. 2011, Kouneiher et al. 2009). Moreover, the prediction that EVC incorporates the intrinsic cost of control is consistent with findings that dACC tracks how aversive control demands are to an individual, including their experienced frustration (Spunt et al. 2012), their preferences against performing the task (McGuire & Botvinick 2010), and how much they devalue rewards associated with the cognitively effortful task (Botvinick et al. 2009a, Cavanagh et al. 2014). Interestingly, dACC has also been found to track the cost of physical effort (Croxson et al. 2009, Hillman & Bilkey 2010, Prévost et al. 2010), suggesting it may play a superordinate role in computing effort-sensitive cost-benefit analyses across domains.

Within the context of the EVC theory, dACC has been further proposed to output signals specifying both the types and amounts of control to allocate in order to maximize EVC; these signals have the effect of licensing the effort required by the allocated control. This prediction is supported by evidence that dACC is able to differentiate between types of control that are needed in a given situation (Kaping et al. 2011, Shen et al. 2014); that changes in dACC activity during monitoring predict subsequent control adjustments (e.g., response slowing, attentional shifts) (Kerns et al. 2004, Shenhav et al. 2016, Ullsperger et al. 2014); and that causal manipulations of dACC can influence these adjustments (Reinhart & Woodman 2014, Sheth et al. 2012; see also Mansouri et al. 2017) or, in extreme cases, more drastically influence one's willingness to engage in control-demanding tasks (i.e., one's decision to deem those tasks worth the effort) (Holroyd & Yeung 2012, Parvizi et al. 2013, Stuss 2011, Walton et al. 2007). For instance, dACC-lesioned rats are less likely to pursue the greater of two rewards if doing so requires overcoming an effortful obstacle (Holroyd & McClure 2015, Walton et al. 2007).

The proposed role of dACC in specifying EVC-maximizing control signals is broadly consistent with many other accounts of this region's role in integrating relevant evaluative signals to help guide adaptive behavior (reviewed in Cavanagh & Frank 2014; Heilbronner & Hayden 2016; Shenhav et al. 2013, 2016; Ullsperger et al. 2014). For instance, the HRL model by Holroyd and colleagues (Holroyd & McClure 2015, Holroyd & Yeung 2012) proposes that dACC learns the value of extended sequences and on that basis determines whether to discount the cost of effortful obstacles that prevent lower-level action selection regions of striatum from persevering over future actions within that sequence. Verguts and colleagues (2015) similarly propose that dACC learns the cost-discounted value of adjusting the gain on action in a given context and modifies processing accordingly. And Alexander & Brown (2015) propose that regions of dACC serve to tune predictions about the errors that will result from failing to act appropriately, failing to maintain the appropriate information in working memory, or both, leading to adaptive improvements in decisions about which information to gate. Although a comprehensive comparison of these models and their ability to account for dACC function is beyond the scope of the current review, these theories show collectively that an appropriately nuanced model of control allocation may provide a more parsimonious account of the variety of signals that have been observed in this region, without having to posit additional unique functions associated with each signal (Shenhav et al. 2016).

4.3. Expected Value of Control and the Broader Executive Network

Two brain regions that are commonly included within the same executive/control network as dACC are AI and lPFC. These have been proposed as inputs to and outputs of control allocation decisions, respectively (Bush et al. 2000, Cai et al. 2016, Shackman et al. 2011, Shenhav et al. 2013, Ullsperger et al. 2014). Like dACC, AI has been shown to respond phasically to a broad array of salient events that may signal the need to adapt control (including rewards and errors) (Menon & Uddin 2010) and also displays sustained elevated responses over the course of task performance (possibly related to the maintenance of control) (Dosenbach et al. 2006). However, these two regions (which share reciprocal connections) differ in their relative patterns of connectivity with sensory inputs versus motor outputs, with AI sharing more connections with the former than the latter (Craig 2009). Accordingly, although substantial evidence of dissociation is still lacking, based on their relative timing and patterns of activation across the literature, dACC may play a more direct role in effecting changes in control allocation, whereas AI may signal salient states that bear on those control allocation decisions (e.g., internal and external signals associated with error commission) (Cai et al. 2016; Craig 2009; Magno et al. 2006; Medford & Critchley 2010; Ullsperger et al. 2010, 2014).

Researchers have shown lPFC plays a key role in the execution or regulation of certain control policies, and they therefore argue it is the executor of specific kinds of control signals that have been specified by dACC (e.g., maintaining task sets) (Botvinick et al. 2001, Holroyd & Yeung 2012, Ridderinkhof et al. 2004, Shenhav et al. 2013). This proposed functional relationship has been supported by studies that examine the timescale of processing across these two regions during control monitoring, adjustment, and execution (Kaping et al. 2011, Oehrn et al. 2014, Tang et al. 2016, Womelsdorf et al. 2010). Like dACC, lPFC has also been found to be associated with preferences to avoid cognitive effort (McGuire & Botvinick 2010) and with signatures of cognitive fatigue (Blain et al. 2016, Tanaka et al. 2014). This may suggest a role in signaling control costs, perhaps at a more abstract or heuristic level (cf. McGuire & Botvinick 2010) but could also suggest that lPFC provides a more sensitive readout of the level of cognitive effort (i.e., control output) being exerted at a given time (Wang et al. 2016).

Although regions of lPFC appear to be the nodes of the executive network most closely associated with the regulation of control, it is important to note that control signals are heterogeneous and their regulation is therefore unlikely to be the sole purview of lPFC. Rather, the execution of control signals is likely mediated by several of dACC's downstream targets that can implement different types of control signals (Shenhav et al. 2013, Ullsperger et al. 2014), including global modulatory changes in response threshold (driven by subthalamic nucleus) (Cavanagh & Frank 2014, Cavanagh et al. 2011, Keuken et al. 2015) and in the gain of neural processing (driven by locus coeruleus) (Aston-Jones & Cohen 2005, Eldar et al. 2013, Jepma & Nieuwenhuis 2011).

It is impossible to discuss the role of cortical and subcortical circuits in effort allocation without also considering the central role of the midbrain dopaminergic system (reviewed in Cools 2016, Salamone et al. 2009, Westbrook & Braver 2016). At shorter timescales, dopaminergic circuits have been shown to discount phasic responses to rewards by the levels of physical or cognitive effort required (Botvinick et al. 2009a, Pasquereau & Turner 2013, Varazzani et al. 2015; but see also Gan et al. 2010). At longer timescales, dopaminergic input to cortex, and to dACC in particular, has been shown to be causally necessary for engagement in effortful behavior (Holroyd & McClure 2015, Salamone et al. 2009, Walton et al. 2007), particularly when the effort requires the agent to overcome a bias toward a salient default alternative (Nicola 2010). For instance, pharmacological attenuation of dopamine levels, or damage to the white matter tracts connecting the nucleus accumbens and cingulate cortex, renders animals less willing to expend effort to achieve a greater reward.

The motivational impairments resulting from dopamine manipulation are similar to those discussed above that result from damage to dACC and, often, adjacent regions of supplementary motor area (SMA). Variability in structural and functional connectivity between dACC and SMA has also been implicated in more subtle manifestations of apathy and their relationship to decisions about physical effort investment (Bonnelle et al. 2015). Most notably, transcranial magnetic stimulation of SMA has been further shown to attenuate the aversive experience of a physically demanding task, rendering participants more willing to exert effort for less reward (Zenon et al. 2015). Collectively, these findings suggest that interactions within and among medial prefrontal cortex and dopaminergic circuits are critical for transforming evaluative inputs into effort investments, both in the physical and cognitive domain (see also Hosking et al. 2014). However, in the final section below, we discuss important questions that remain regarding the degree of neural and computational overlap that exists across these domains.

5. CHALLENGES AND FUTURE DIRECTIONS

As our review shows, there is an exciting confluence of research on the computational and neural basis of control costs and our ability to allocate control while accounting for these costs. Yet several important questions remain to be addressed.

5.1. Operationalizing and Measuring Cognitive Effort

First, although overwhelming evidence suggests that control is costly, it is far from clear how those costs should be operationalized (i.e., what are their constituents) or, more importantly, how they should be measured. Control costs have been inferred from a variety of measures including response times (RTs) (Anderson 1996, Lieder et al. 2014, Ratcliff 1978, Sternberg 1969), avoidant preferences (Kool et al. 2010, McGuire & Botvinick 2010, Westbrook et al. 2013), affective priming (Dreisbach & Fischer 2015), pupil diameter (Kahneman & Beatty 1966), contraction of specific facial muscles (corrugator supercilii) (Elkins-Brown et al. 2015), sympathetic arousal (Critchley et al. 2003), and neural activity measured from dACC (Cavanagh & Frank 2014, Cavanagh et al. 2014, McGuire & Botvinick 2010, Spunt et al. 2012) and other regions (Blain et al. 2016, McGuire & Botvinick 2010; reviewed in Inzlicht et al. 2015, Westbrook & Braver 2015). However, none of these measures has been shown to be selective to control costs; rather, many have been shown to index other, more general, factors such as sympathetic arousal. Even a seemingly direct measure such as demand avoidance can be susceptible to ancillary factors related to experimental demand and one's ability or motivation to detect the presence of control cost differences across tasks (Gold et al. 2014). Moreover, some of these measures may be sensitive to both the costs of control and the control being allocated, thus confounding their interpretation as reflecting one or the other. For instance, longer RTs could reflect a more difficult task (i.e., indicating higher cost) or less effort (i.e., indicating that a low level of control was allocated).

Complicating matters further, there is ample evidence that cognitive effort can have positive associations in addition to the aversive ones described above and that this may differ considerably across individuals. For example, certain contexts or personality traits [e.g., need for cognition (Cacioppo & Petty 1982), learned industriousness (Eisenberger 1992)] will lead an individual to associate mental effort exertion per se with reward, independent of the outcome of the effort. Moreover, it is well known that people find tasks requiring low levels of cognitive engagement to be boring and therefore aversive, and they instead seek to find an optimal midpoint between too little and too much cognitive effort (Nakamura & Csikszentmihalyi 2002). Whereas the former examples link reward more directly to effort exertion—leading to predictions that are difficult to dissociate from intensity-based control cost predictions—boredom has been proposed to instead be a reaction to low levels of information or arousal in certain environments (Eastwood et al. 2012; Geana et al. 2016a,b; Zakay 2014) and is therefore potentially more readily dissociated from control costs. Dissociating these cost and reward functions will require careful experimental design and measurement of participant-specific estimates of reward and effort.

These concerns regarding measurement and overlapping cost and reward functions highlight the importance of generating precise and quantitative predictions regarding the factors influencing control allocation and then constraining these predictions with multiple clearly specified predictor variables. In addition to the aforementioned measures, this naturally includes measuring self-reported subjective experiences of effort. It remains an open question whether conscious awareness is a prerequisite for treating the exertion of control as costly (cf. Desender et al. 2014, Dunn et al. 2016, Mulert et al. 2005, Naccache et al. 2005) and whether cognitive control even functions in part to regulate these negative experiences (Inzlicht et al. 2015). Regardless, subjective measures can undoubtedly help constrain a theory by identifying similarities and differences between task- and context-related variables that trigger different kinds of avoidant reactions and thereby define a topology of subjective experiences characterized by terms such as difficult, frustrating, tiring, stressful, challenging, and boring (cf. Saunders et al. 2015, Spunt et al. 2012). They may also help tease apart the components of control costs that relate to effort per se from other aversive reactions associated with individual control demands, such as errors and conflict or uncertainty.

5.2. Disentangling Competing Models and Mechanisms

Another critical step is for models of control costs and control allocation to be compared with one another directly, which in turn will require models to reconcile differences in relevant terminology. This process is likely to reveal similarities or even substitutability in individual algorithms, as well as substantive differences at the levels of theory, implementation, or both. The goal should be to generate common benchmarks for these varied models in terms of both selection and execution of control and to perform dedicated experiments that examine which model best predicts how people allocate mental effort. For instance, future research should evaluate more carefully the extent to which control cost increases (*a*) monotonically with control signal intensity and duration (Musslick et al. 2015, Shenhav et al. 2013); (*b*) with the richness of context required to support nondefault responses (as indexed by the difference between the distribution of potential responses for the controlled versus automatic policy) (Ortega & Braun 2011, 2013); and/or (*c*) with the value of opportunities foregone while engaged in candidate computations (Kurzban et al. 2013; Lieder et al. 2014; F. Lieder & T.L. Griffiths, submitted manuscript).

Such model comparison will further aid efforts to interpret the role of neural mechanisms that have been implicated in control allocation and generate more precise predictions regarding the time-course of activation across regions in response to signals that demand a change in control settings. This will in turn help to settle longstanding debates regarding the functional role or roles of dACC and other regions across research into decision making, cognitive control, and affective processing (Heilbronner & Hayden 2016; Holroyd & Yeung 2012; Shackman et al. 2011; Shenhav et al. 2013, 2016). It will further help to constrain predictions for a given theory regarding how to interpret dACC's often underdetermined engagement in a particular context—for instance, whether it reflects the costs, demands, and/or output of control (Shenhav et al. 2013).

5.3. Relationship Between Different Forms of Effort

Attempts to understand the computational and neural underpinnings of cognitive effort frequently draw connections to those same underpinnings for physical or motor effort. This may be unavoidable given the empirical links between the phenomenology and mechanisms of these two forms of effort (Marcora et al. 2009, Schmidt et al. 2012), but it prompts a very important question: If physical effort is in fact associated with physical resource depletion (Cabanac 2006), and cognitive effort turns out not to be (Inzlicht & Schmeichel 2012, Kurzban et al. 2013), then why are there similar underpinnings for these two? A provocative possibility is that the costly component of physical effort in fact has little to do with physical resources (Marcora 2009, Marcora & Staiano 2010, cf. Huang et al. 2012) but rather is a similar control cost as for cognitive control—the cost of overcoming a more automatic option (e.g., more habitual behavior). Given the fundamental nature of the relationship between these two forms of effort, future work should better characterize their respective cost functions and the basis for any similarities among these. This work should also aim to compare the degree to which different species discount rewards for a similar amount of cognitive or physical effort.

5.4. Clinical and Policy-Related Applications

Appropriate allocation of cognitive effort is central to our ability to thrive as humans, particularly given the demands of modern environments. Individuals who are willing and/or able to exert control more consistently and in spite of apparent obstacles are able to perform better in academic and work environments (Duckworth et al. 2007, Eigsti et al. 2006, Mischel et al. 1989). Conversely, varieties of impairments in control allocation resulting from disorders such as major depression, schizophrenia, addiction, obsessive-compulsive disorder, and attention-deficit disorder can be particularly debilitating (Cools 2016, Holroyd & Umemoto 2016, Salamone et al. 2016, Westbrook & Braver 2015).

Yet even high-functioning individuals are prone to failing to exert the control required to override habitual, impulsive, and other short-sighted response tendencies; such self-control failures have serious ramifications for the health, safety, relationships, educational attainment, and finances of these individuals (Duckworth et al. 2007, Heatherton & Wagner 2011, Mischel et al. 1989) and even the evolution of our species (Cohen 2005, Tomlin et al. 2015). From the perspective of bounded optimality, some of these failures might be inevitable in complex environments with too many misleading temptations because people's cognitive resources are finite and their time is limited. Indeed, tolerating occasional self-control failures may be more boundedly optimal than ensuring such failures never occur.

According to this view, people should instead restructure their environment so that good decisions can result from simple heuristics rather than requiring extensive cognitive operations (Gigerenzer 2008, Lieder & Griffiths 2016). One example of this approach that has proved effective is to impose default options for certain decisions that maximize the typical decision maker's long-term rewards (e.g., retirement savings), a policy referred to as paternalistic libertarianism (Thaler & Sunstein 2008). Another approach is to align the immediate rewards of each choice with its long-term value, potentially enabling people to rely on automatic, short-sighted decision mechanisms instead of having to override them and instead engage effortful long-term planning (Lieder & Griffiths 2016). These approaches offer useful directions for policies aimed at improving people's ability to deploy cognitive effort adaptively within complex environments.

Formal models of control allocation offer a critical path forward in understanding the mechanisms by which individuals succeed or fail at achieving the desired return on their cognitive effort investment. These models can provide insight into how to make the control allocation most appropriate to the task at hand—for instance, by improving strategies for learning about the value of exerting cognitive effort and how it depends on different attributes of the task or situation. In addition, such models may also provide insights into how to make control less costly, for instance, by allowing people to rely more on processes that are well learned and overlap minimally with other processes that may need to be engaged. These models might therefore facilitate the design of interventions to improve the allocation of cognitive control and restructure the environment to maximize the likelihood that attempts at control succeed in their goals. Advances in modeling and empirical validation of such interventions will redound to our improved understanding of the mechanisms underlying cognitive effort allocation, bringing us closer to answering the age-old question of what makes it hard to think and what can we do about it.

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