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Decomposing the Motivation to Exert Mental Effort

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Abstract
Achieving most goals demands cognitive control, yet people vary widely in their success at meeting these demands. Although motivation is known to be fundamental to determining success at achieving a goal, what determines motivation to perform a given task remains poorly understood. Here, we describe recent efforts toward addressing this question using the expected-value-of-control model, which simulates the process by which people weigh the costs and benefits of exerting mental effort. This model functionally decomposes this cost-benefit analysis and has been used to fill gaps in understanding of the mechanisms of mental effort and to generate novel predictions about the sources of variability in real-world performance. We discuss the opportunities the model provides for formalizing hypotheses about why people vary in their motivation to perform tasks, as well as for understanding limitations in researchers' ability to test these hypotheses using a given measure of performance.

Keywords
motivation, cognitive control, reward, punishment, decision making, self-efficacy, achievement

Achieving most goals—whether they involve future college admissions, job positions, or funding opportunities—requires allocating the mental resources needed to perform well on the tasks leading to those goals. Yet people vary widely in how they perform on those tasks, and therefore in the degree to which they succeed in reaching their goals. Why is that the case? Classically, answers to this question focused on the cognitive resources at a person's disposal, that is, the person's *ability* to perform the task at hand. Did the person have the appropriate knowledge and know-how, and were those resources at full capacity, or were they drained by biological factors (e.g., hunger, fatigue) or environmental factors (e.g., distractors)? It has since become widely acknowledged that *motivation* serves an equally important role in determining how people will vary in their performance (Braver et al., 2014; Duckworth & Carlson, 2013; Shenhav et al., 2017). And yet, how it is that people become motivated to invest their cognitive resources in a given task remains something of a mystery.

Mental Effort as the Product of a Cost-Benefit Analysis

At the broadest level, motivation entails an interaction between a goal (e.g., loading boxes into a truck), an obstacle to that goal (e.g., the weight of the boxes), and a force required to overcome that obstacle (e.g., the contraction of muscles). For cognitively demanding tasks, the forces in question are forms of *cognitive control*, mechanisms that enable people to flexibly process information, for instance, to selectively attend to some aspects of the environment while suppressing others (Botvinick & Cohen, 2014). Motivation further entails a key limitation on the application of force: a *cost*. People tend to prefer tasks that require less cognitive control (i.e., those that are less mentally effortful;

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Chong et al., 2016; Kool & Botvinick, 2018; Shenhav et al., 2017). These costs can, however, be outweighed by the potential *benefits* of exerting effort: The larger the potential compensation, the more willing a person is to perform a cognitively demanding task (Kool & Botvinick, 2018; Westbrook et al., 2013). To understand how and why people vary in their performance across tasks, it is therefore critical to understand how they weigh these costs and benefits.

A Model-Based Framework for Evaluating the Costs and Benefits of Mental Effort

We recently developed a computational model that formalizes this cost-benefit analysis (Shenhav et al., 2013), to describe how a person chooses to invest mental effort (e.g., in the case of a student deciding how hard to study for an exam). To do so, we integrated insights from two bodies of research that had addressed complementary aspects of this problem: research on how people make cost-benefit decisions and on how they adjust cognitive control to meet the demands of a given task.

Earlier research on decision making had characterized general-purpose algorithms for how people evaluate the expected value of a given action, taking account of its costs and benefits and the probabilistic structure of the environment. Although elements of these expected-value calculations had figured prominently throughout classic theories of motivation (Atkinson, 1957; Bandura, 1977; Brehm & Self, 1989; Vroom, 1964), laying the foundation for their application to the study of mental-effort allocation, those theories lacked grounding in explicit mechanisms underpinning the execution of mental effort (i.e., the cognitive musculature). A parallel body of research had rigorously characterized the structure of cognitive control, formalizing the process by which information is processed over the course of a task and how that information processing is adjusted by different forms of control (Botvinick & Cohen, 2014). The resulting models provided quantitative estimates of variability in task performance (e.g., speed and accuracy) as a function of the stimuli, the task requirements, and the state of the control system. However, this research had yet to explain how people decide that cognitive control is *worth* allocating.

Our model bridges these two research areas by describing how people decide to allocate a certain amount of control in a given situation, what impact these decisions have on their performance, and how they learn from the outcomes of their efforts how much control to allocate in similar future situations. Specifically, our model simulates individual task environments and the range of performance a hypothetical person could achieve on these tasks (Fig. 1; Lieder et al., 2018; Musslick et al., 2015). At one extreme is performance if minimal control is invested into the task, such that the person relies primarily on automatized, habitual modes of processing the stimuli. At the other extreme is performance if the person maximizes control. The spectrum of performance that results therefore depends heavily on the task requirements and how automatized a given element of the task is for that individual (i.e., the person's skill level), which is determined by innate and learned factors. According to our model, the person decides what level of control to allocate to the task by weighing expected payoffs against the cost of exerting the associated levels of mental effort in the current context; we refer to the difference between the cost and payoff as the *expected value of control* (EVC; Shenhav et al., 2013). Using this model, we have been able to simulate the process by which people consider the incentives and task demands in a given environment to choose what task (or tasks) to perform and how much control to invest when performing them. These simulations have allowed us to reproduce behavioral patterns that have been previously observed under similar task conditions (Lieder et al., 2018; Musslick et al., 2015, 2019).

The EVC model provides a framework for formulating and testing predictions about how people become motivated to engage in particular tasks, and when and why they may be insufficiently motivated for the task at hand. The model formalizes key elements of this cost-benefit analysis, including the different ways that a person could allocate control in a given situation, the relevant future outcomes, and the influence control will have in achieving some outcomes and avoiding others (Fig. 2). Recent work has shown how powerful this functional decomposition can be for identifying and filling gaps in the experimental literature, and for building and refining predictions about the role motivation plays in shaping cognition.

Filling Gaps in Understanding of the Mechanisms of Mental Effort

Over the past few decades, research has focused on unraveling the mechanisms underlying motivation-control interactions. To do so, this work has focused in large part on the ultimate driver of effort: potential rewards. A consistent finding in this literature is that when there is greater reward on offer, people tend to invest more effort in a task, as reflected in better performance (e.g., faster and more accurate responding) and greater activation of control circuitry (Parro et al., 2018). However, this emphasis on the rewards for good

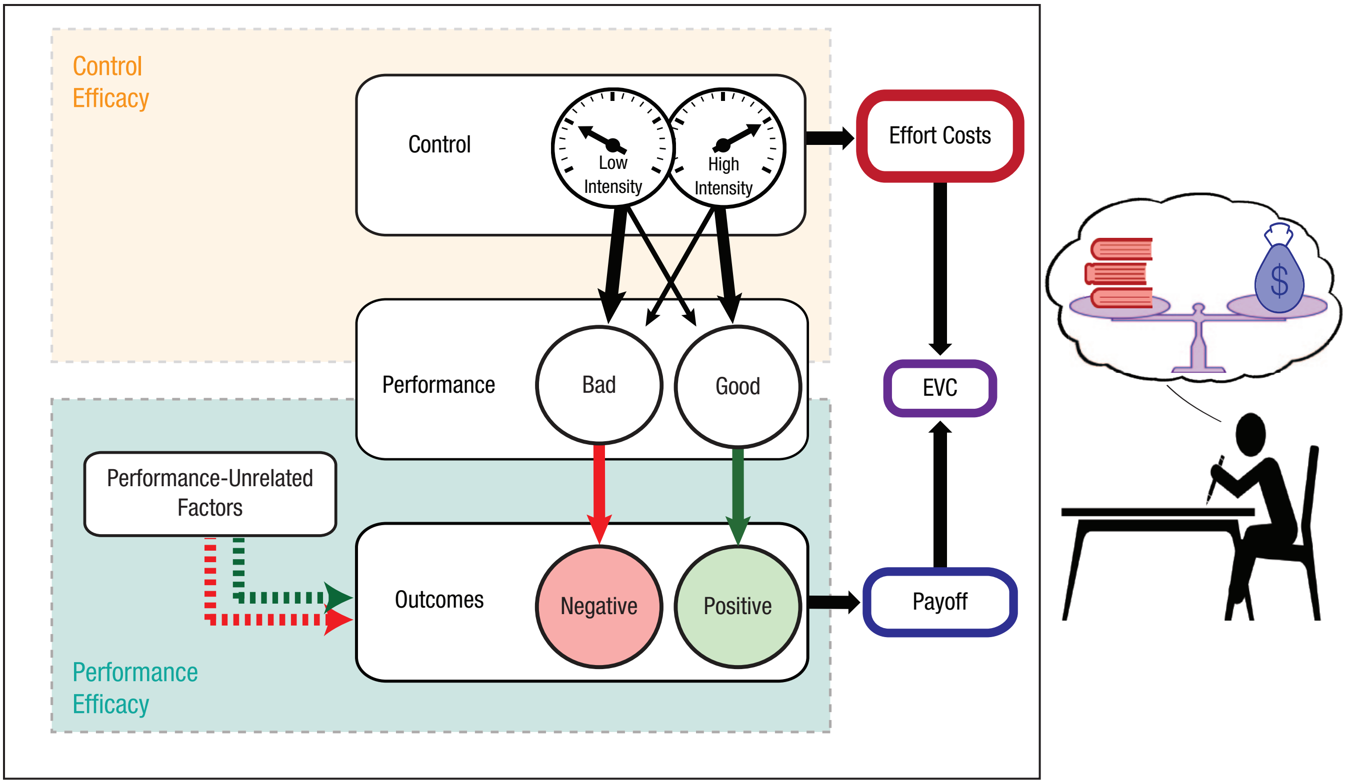

Fig. 1. The expected-value-of-control (EVC) model. According to this model, people determine how to exert mental effort by weighing the costs and benefits of allocating cognitive control in a particular way given their current situation. Cognitive control is allocated along two dimensions: the types of control being engaged (e.g., attention to specific features of a task, suppression of inappropriate responses) and how intensely each of these is engaged. This diagram illustrates the model in the case of hypothetical control signals of high versus low intensity (locations of the arrows on the gauges); downward arrows reflect the likelihood of achieving bad versus good performance (thicker arrows indicate higher likelihood) and the likelihood of achieving negative versus positive outcomes with a given level of performance. The model assumes that people experience greater intensities of control as more mentally effortful, and therefore more costly (for a discussion of potential sources of these costs, see Shenhav et al., 2017). The overall value of a given control allocation (EVC) within the current context is determined by weighing the costs of exerting effort against the expected payoff for exerting that effort. This payoff is determined by the expected outcomes (e.g., monetary gain or loss, social approval or admonishment), weighted by the extent to which mental effort matters for attaining these outcomes. Control efficacy refers to the extent to which increasing the intensity of control changes the likelihood of performing well on a task (relative thickness of the black arrows). Performance efficacy refers to the extent to which outcomes are determined by performance or by unrelated factors such as the person's social status (relative thickness of the dashed vs. solid red and green arrows). If greater control has little bearing on performance (i.e., low control efficacy) or if outcomes are expected to be largely determined by factors unrelated to performance (i.e., low performance efficacy), then a high level of control will not be deemed worthwhile. Each of these components can also have some uncertainty around it (not shown here). For instance, even when outcomes are completely determined by performance, there may be some uncertainty about whether a given outcome will come to pass.

performance overlooks key sources of real-world mental-effort motivation that our model further unravels.

Disentangling different means of achieving different ends

When deciding how to allocate their mental effort, people consider a multitude of potential outcomes and a multitude of strategies for achieving those outcomes. They are motivated by the positive outcomes that effort can achieve (e.g., wealth, praise, pride), but also often equally or even more motivated by the potential negative outcomes that effort avoids (e.g., loss, rejection, disappointment; Atkinson, 1957). People also consider how these outcomes can be achieved or avoided by adjusting not only how much effort they invest but also how they invest it. For instance, they may choose to adjust what they attend to (e.g., how much effort they put into focusing on the task vs. suppressing the impulse to check social media) and what strategies they prioritize when completing the task (e.g., getting everything done either quickly or accurately).

The EVC model links considerations of which outcomes to achieve with considerations of which types of control will best achieve those outcomes. In doing so, it provides a potential account of inconsistencies in the experimental literature as well as ways of testing this account. In particular, unlike research on potential

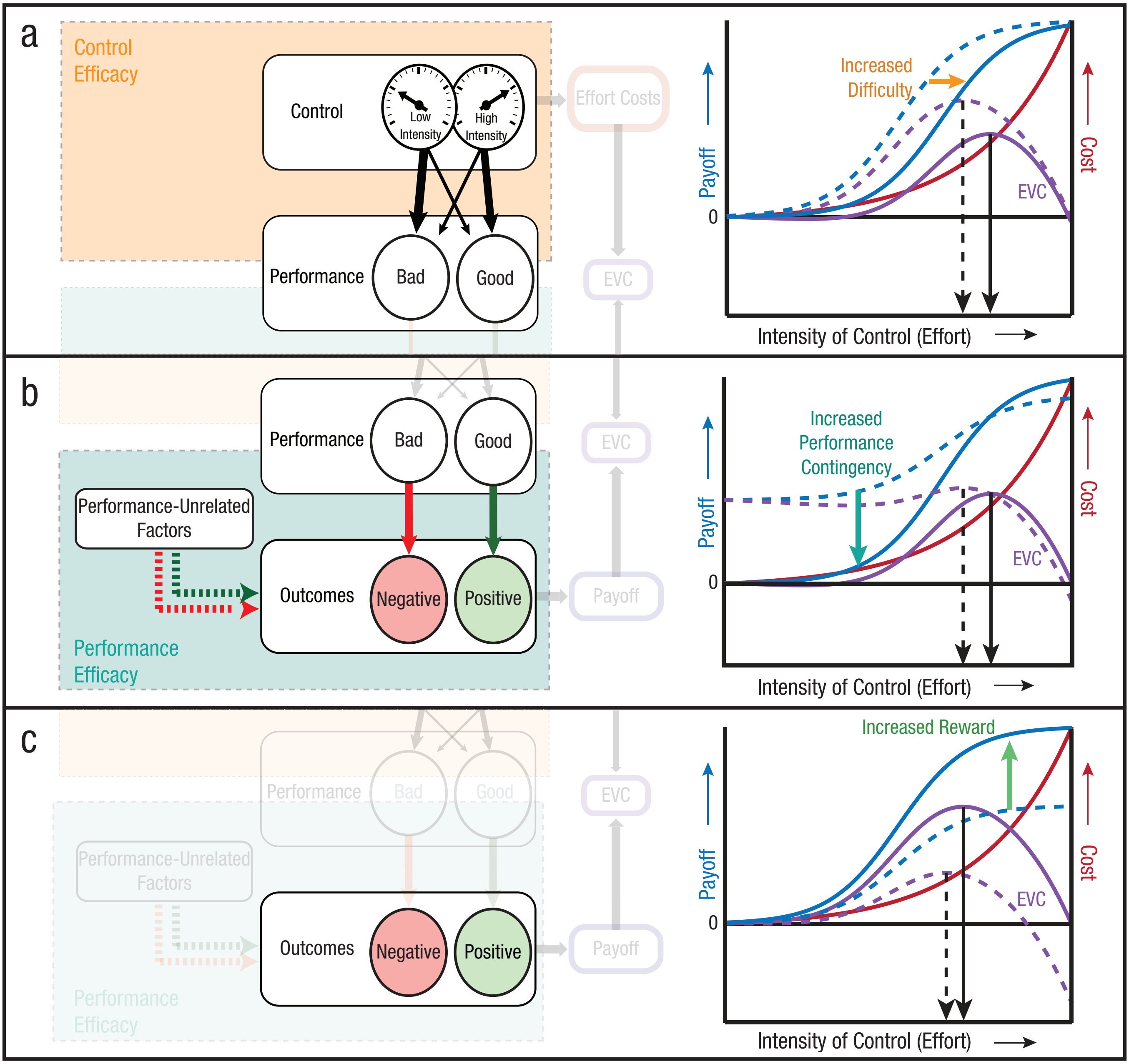

Fig. 2. Formalization of the components of mental-effort motivation. According to the expected-value-of-control (EVC) model, how much effort a person invests in a given task is jointly determined by the person's expectations of (a) control efficacy (e.g., how difficult the task is relative to the person's own skill level), (b) performance efficacy (e.g., how likely it is that the person will be evaluated on the basis of performance), and (c) outcomes (e.g., how much the person cares about being evaluated positively and/or being evaluated negatively). The graphs on the right show how changes in each of these components affect the evaluation and allocation of control. Each graph shows EVC as a function of control intensity (purple curves), calculated by subtracting the expected effort costs (red curves) from the expected payoffs (blue curves). The optimal level of control to invest is the one that maximizes EVC (vertical black arrows). In addition to being associated with higher effort costs, higher control intensities typically yield better performance, which typically yields better outcomes (i.e., higher payoffs). The graphs illustrate how the shapes of the payoff curves differ when people expect lower (dashed blue lines) versus higher (solid blue lines) levels of task difficulty (i.e., whether a small vs. large amount of control will be needed to achieve a given level of performance), performance contingency (i.e., whether payoffs will depend less vs. more on a given level of performance), and reward magnitude (i.e., whether the peak of the payoff curve at the highest levels of performance is low vs. high). The purple curves and black arrows show the EVC functions and corresponding optimal levels of control when task difficulty, performance contingency, and reward magnitude are high (solid lines) versus low (dashed lines). See Figure 1 for further details regarding the diagrams on the left. The graphs on the right are adapted from Shenhav et al. (2013), p. 227, and Frömer et al. (2021), p. 2. Adapted with permission from Elsevier.

rewards for control, the more limited literature on responses to potential negative outcomes has reported mixed patterns of behavior and neural activity, including both speeding and slowing of responses (Cubillo et al., 2019; Ličen et al., 2016; Yee et al., 2016). The EVC model offers a potential explanation for these apparent inconsistencies: The value of potential outcomes can signal the need to adjust both how much and what kind of control to engage. A recent study from our lab tested the model's prediction that different types of control can be adaptive depending on the relative incentives for achieving correct responses and avoiding incorrect responses (Leng et al., 2020). Participants were allowed to complete as many trials of the assigned task as they wanted within a fixed period of time, so they had the freedom to choose how much to emphasize speed and accuracy. The EVC model predicted that increasing rewards for a correct response would lead participants to adjust their control in a way that increasingly favored both speed and accuracy, whereas increasing penalties for errors would lead them to selectively favor accuracy over speed. The experimental findings confirmed these model predictions.

Disentangling different paths between means and ends

Decisions about how to allocate mental effort are clearly determined to a significant degree by how good or bad the outcomes could be. However, just as important is how much one's efforts matter for bringing about those outcomes. Sometimes, increasing cognitive control is unnecessary, ineffective, or entirely irrelevant to whether desirable outcomes are achieved and undesirable ones avoided. The EVC model teases apart the formally distinct elements of what can be broadly referred to as the *efficacy* of effort, distinguishing between how cognitive control translates into performance and how performance translates into ultimate outcomes (Figs. 2a and 2b; cf. Bandura, 1977; Vroom, 1964).

One factor that determines how much one's effort matters is the extent to which greater cognitive control (i.e., larger investments of mental effort) translates into better performance. This factor, which we refer to as *control efficacy*, is determined by a person's skill at the task at hand (as shaped by a combination of innate ability and practice) as well as the level of difficulty of the task (Fig. 2a). However, as college, job, and grant applicants are aware, even the best performance does not guarantee the best outcomes. How much one's effort matters is also a function of *performance efficacy*, the extent to which potential outcomes are determined by performance on a given task, as opposed to performance-unrelated factors, such as reviewer bias (Fig. 2b).[1] These latter factors do not influence whether a given level of effort is sufficient to perform well (as in the case of control efficacy), but rather influence whether performing well is even relevant for achieving a good outcome and/or avoiding a bad one. In other words, as expected performance efficacy decreases, effort seems increasingly pointless. Efficacy estimates thus rely on subjective perceptions of one's own skill and competence and the demands of the task (control efficacy), as well as one's agency and the controllability of one's environment (performance efficacy; Bandura, 1977; Brehm & Self, 1989; Dweck & Leggett, 1988; Graham, 1991; Ly et al., 2019).

Recent work on motivation-control interactions has indirectly tapped into efficacy expectations by studying the influence of expected task difficulty on performance. Studies have shown behaviorally and neurally that people tend to invest more effort when they expect the upcoming task to be more difficult (Jiang et al., 2015; Krebs et al., 2012). However, in these studies, expected difficulty is varied while expected performance efficacy is held constant, so they only tap into the relationship between control and performance (control efficacy), and they do so in a nonmonotonic (U-shaped) fashion, as control efficacy increases from low to moderate levels of difficulty but then decreases at especially high levels of difficulty (Brehm & Self, 1989). Recent studies from our lab have begun to address this gap by examining the mechanisms by which control allocation varies as a function of the expected efficacy of performance when expected control efficacy (e.g., task difficulty) is held constant (Frömer et al., 2021; Grahek, Frömer, & Shenhav, 2020; see also Manohar et al., 2017). Specifically, these studies varied the extent to which participants could expect reward to be *performance contingent* (i.e., determined by performing well at the task) or not (i.e., determined at random). Confirming our model's predictions, behavioral and neural measures of control in these studies showed that participants integrated expected levels of reward and performance efficacy and invested more effort the more they expected performance to be both rewarding and efficacious.

Explaining Variability in Cognitive Performance: Opportunities and Constraints

By decomposing motivation into formal components, the EVC framework not only provides a path toward disentangling the mechanisms driving each of those components, but also offers a richer hypothesis space for predicting how variability in these components contributes to variability in cognitive performance across individuals and contexts. For instance, in studying motivational impairments that are prevalent in disorders such as depression and schizophrenia, researchers have focused on the extent to which individuals with these disorders may undervalue the expected rewards for their efforts and/or overvalue the associated effort costs (Chong et al., 2016). The EVC model provides a means of generating and testing hypotheses about alternate sources of motivational impairments, such as an overvaluation of potential negative outcomes for poor performance (which may lead to excessive caution) or misperception of the extent to which that performance determines one's outcomes (Grahek et al., 2019). The EVC model also clarifies the means by which one's investment of effort—whether in the classroom or the workplace—might be shaped by one's past experiences (Bustamante et al., 2021; Grahek, Frömer, & Shenhav, 2020; Lieder et al., 2018). For instance, growing up in a volatile environment could downwardly bias one's perceptions of performance efficacy in future task environments, and growing up in a resource-poor environment could downwardly bias expected rewards for one's efforts (Dweck & Leggett, 1988; Graham, 1991; Ly et al., 2019).

These hypotheses are speculative, but this model-based framework fleshes them out (see the graphs in Fig. 2), enabling researchers to simulate the real-world outcomes that might result from each of these different sources of variability, and to probe the relevant processes in targeted experiments. Applying this approach, studies have recently simulated different ways in which changes in one's mood could theoretically alter one's motivation to engage with a task (e.g., by making a task seem easier or harder; Grahek, Musslick, & Shenhav, 2020).

The EVC model thus provides the means to generate a wide variety of theoretically distinct hypotheses for why people distribute their mental efforts in a particular way. Beyond that, even within a given experiment, it can offer alternative explanations for a single experimental finding. For instance, the fact that Participant A asks to be compensated more to perform a difficult task than Participant B does (cf. Westbrook et al., 2013) is often interpreted as A experiencing mental effort as more costly. But it is also possible that, relative to B, A has lower expectations about the likelihood of performing well at the task (Fig. 2a) or places greater weight on avoiding failure (Fig. 2c). This example also assumes that people always experience effort as costly, when in fact there are a variety of circumstances in which people prefer the experience of a mentally demanding task over a less demanding one (Inzlicht et al., 2018). Participant B may therefore prefer engaging in the more difficult task *because* of how much effort it requires rather than despite the effort.

These varied hypotheses also underscore that even simple measures of task performance are multiply determined. This in turn raises a troubling question: Is it even possible to tease these hypotheses apart from one another? Fortunately, a model-based approach provides a path toward addressing such a concern. Because the EVC model is able to estimate how performance varies as a function of different model parameters (e.g., expected outcomes vs. expected performance efficacy), it can also be used to answer a different but related question: How likely is it that one source of performance variability will be confused with another? For instance, by simulating a population of individuals who vary in their ability and/or motivation to perform different tasks, studies have quantified how reliably individual differences in a given element of motivation or ability (e.g., the cost of control) can be estimated from the individuals' performance on a given task (Musslick et al., 2018), as well as which task measures are best suited for indexing the individual difference of interest (Musslick et al., 2019). This approach has value both as a psychometric tool and as a means of constructing and validating novel tasks that better tap into the cognitive and motivational processes that underlie variability in real-world performance.

Concluding Remarks

These final points underscore the inherent complexities in measuring one's motivation to exert mental effort. As difficult as these inference problems can be in a controlled experiment, they are only magnified when researchers move outside of the lab. The EVC model lays bare these complexities and identifies avenues for teasing apart the underlying mechanisms. Furthermore, these avenues provide opportunities for testing and potentially falsifying the model's core assumptions, and for deepening understanding of the complexities of control allocation that the model has yet to address. For instance, it remains unknown what the costs of engaging in the cost-benefit calculation are and to what extent those costs encourage people to generate rough approximations to EVC and/or use simplifying heuristics to decide when to engage control. A person may, for example, settle on default control policies for situations that generally merit a certain level of control (cf. Gollwitzer, 1999), even if this may result in sometimes exerting more effort than the reward is worth (cf. Bustamante et al., 2021). Addressing this broader set of questions will be a considerable challenge, but the benefits will surely outweigh the costs.

Recommended Reading

Frömer, R., Lin, H., Dean Wolf, C. K., Inzlicht, M., & Shenhav, A. (2021). (See References). Reports a series of behavioral studies that demonstrate that people integrate expectations of reward and performance efficacy to adjust their allocation of mental effort, as well as an electroencephalography study that identifies neural signatures of this integration process.

Moscarello, J. M., & Hartley, C. A. (2017). Agency and the calibration of motivated behavior. *Trends in Cognitive Sciences, 21*(10), 725–735. Reviews the literature on how controllability of positive or negative events drives goal-directed behavior.

Parro, C., Dixon, M. L., & Christoff, K. (2018). (See References). Presents a meta-analysis of functional MRI studies on motivated cognitive control, revealing the brain networks that support the adjustment of cognitive control on the basis of expected reward.

Shenhav, A., Musslick, S., Lieder, F., Kool, W., Griffiths, T. L., Cohen, J. D., & Botvinick, M. M. (2017). (See References). Reviews the neural and computational underpinnings of mental effort, including potential sources of effort costs and different models of control allocation.

Yee, D. M., & Braver, T. S. (2018). Interactions of motivation and cognitive control. *Current Opinion in Behavioral Sciences, 19*, 83–90. Presents an accessible summary of the different ways in which motivation can act on cognitive control and the divergent influences dopaminergic pathways play in modulating these motivation-control interactions.

Transparency

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Note

1. Note that the distinction we are drawing between control efficacy and performance efficacy overlaps conceptually with previous distinctions between, for instance, self-efficacy and expectancy (Bandura, 1977) and between expectancy and instrumentality (Vroom, 1964).

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