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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. While motivation is known to be fundamental to determining these successes, what determines one's motivation to perform a given task remains poorly understood. Here, we describe recent efforts towards 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. By functionally decomposing this cost-benefit analysis, this model has been used to fill gaps in our 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 our ability to test these hypotheses based on a given measure of performance.

Keywords

motivation; cognitive control; reward; punishment; decision-making; self-efficacy; achievement

Whether they involve future colleges, jobs, or funding opportunities, achieving most goals requires that we allocate the mental resources needed to perform well on the ensuing tasks. 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 a person had at their disposal, that is, their *ability* to perform the task at hand. Did they 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 into a given task remains something of a mystery.

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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 us to flexibly process information, for instance selectively attending some aspects of our 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*) (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, to describe how a person chooses to invest their mental effort, for instance in the case of a student deciding how hard to study for an exam (Shenhav et al., 2013). To do so, we integrated insights from two bodies of research that had addressed complementary aspects of this problem- how people make cost-benefit decisions, and 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 one's environment. While 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 with varying 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, task set, and the state of the control system. However, this research had yet to explain how people decided 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; what impact these decisions have on their performance; and how they learn from the outcomes of their efforts to guide future decisions about how much control to allocate in that situation. Specifically, our model simulates individual task environments and the range of performance a hypothetical person could achieve on this task

(Fig. 1; Lieder et al., 2018; Musslick et al., 2015). At one extreme is their performance if they invest minimal control into the task, relying primarily on automatized/habitual modes of processing the stimuli. At the other extreme is the agent's performance if they maximize their control output. 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., their skill level), based on innate and learned factors. Our model proposes that the person decides what level of control to allocate to the task by weighing the expected payoff against the cost of exerting the associated mental effort in their context; we refer to the difference between these 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(s) to perform and how much control to invest when performing them, allowing us to reproduce patterns of behavior that have been observed across labs (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 what influence control will have in achieving some outcomes and avoiding others (Figs. 1–2). 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 our Understanding of the Mechanisms of Mental Effort

Over the past few decades, research has begun to unravel 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 people tend to invest more effort in a task when there is greater reward on offer, 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 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 our mental effort, we consider a multitude of potential outcomes and a multitude of strategies for achieving those outcomes. We are typically not only motivated by the positive outcomes that effort can achieve (e.g., wealth, praise, pride), but often equally or even more motivated by the potential negative outcomes that effort avoids (e.g., loss, rejection, disappointment) (Atkinson, 1957). We also consider how these outcomes can be achieved or avoided not only by adjusting how much effort we're investing but also how we are choosing to invest it. For instance, we may choose to adjust what we are attending to (e.g., focus on the task, suppress the impulse to check social media) and we may choose to prioritize getting everything done either quickly or accurately.

EVC links these two considerations: the evaluation of different types of control in the service of achieving different types of outcomes (Fig. 1, Fig. 2C). In doing so, it provides a potential account of inconsistencies in the experimental literature as well as ways of testing those accounts. In particular, unlike research on potential rewards for control (described above), the more limited set of studies that have examined responses to potential negative outcomes have observed 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 - namely that the value of potential outcomes can signal the need to adjust both *how much* and *what kind* of control to engage. We recently 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). We designed a task that allowed participants to complete as many trials as they wanted within a fixed period of time, giving them the freedom to choose how much to emphasize speed and/or accuracy. Our model predicted that higher rewards for a correct response would lead participants to adjust their control in a way that increasingly favored speed *and* accuracy, whereas higher penalties on errors would lead them to selectively favor accuracy over speed. Our experimental findings confirmed these model predictions.

Disentangling different paths between means and ends

Our 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 our efforts *matter* for bringing about those outcomes. Sometimes, increasing our cognitive control is unnecessary, ineffective, or entirely irrelevant to whether we achieve desirable outcomes and avoid undesirable ones. The EVC model teases apart the formally distinct elements of what can be broadly referred to as the *efficacy* of our efforts, distinguishing between whether these relate to the translation of cognitive control into performance or to the translation of performance into the ultimate outcomes (Fig. 2A–B) (cf. Bandura, 1977; Vroom, 1964).

One factor that determines how much one's effort matters is the extent to which higher intensities of control (i.e., greater investments of mental effort) translate into better performance. This factor, which we will refer to as *control efficacy*[1], is determined by a person's skill at a particular type of task (as shaped by a combination of innate ability and practice) as well as the level of difficulty they are currently attempting (Fig. 2A). However, as applicants to colleges, jobs, and grants 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 how well they perform a given task, versus by performance-unrelated factors, such as reviewer subjectivity/bias (Fig. 2B). These factors do not affect whether a given level of effort is sufficient to perform well (as in the case of *control efficacy*), but rather whether performing well is even *relevant* for achieving a good outcome and/or avoiding a bad one. In other

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

words, as expected *performance efficacy* decreases, effort seems increasingly pointless. Efficacy estimates thus rely on subjective perceptions of one's own skill, competence, and demands of the task (control efficacy) as well as their agency and the controllability of the 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, this approach only taps into the relationship between control and performance (control efficacy), and in fact does so in a nonmonotonic (U-shaped) fashion (control efficacy is highest when difficulty is moderate and lowest when difficulty is very low or very high; Brehm & Self, 1989). To address this gap, we have recently begun to examine the mechanisms by which control allocation varies as a function of the expected efficacy of performance, while holding expected control efficacy (e.g., task difficulty) constant (Frömer et al., 2021; Grahek, Frömer, et al., 2020) (see also Manohar et al., 2017). Specifically, we varied the extent to which participants could expect reward to be determined by performing well at the task or whether it would be determined at random. Confirming our model's predictions, behavioral and neural measures of control in these studies show that participants integrate expected levels of reward and performance efficacy to invest more effort the more they expect 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, it also offers a richer hypothesis space for predicting how variability across these components contributes to variability in cognitive performance across individuals and contexts. For instance, in studying motivational impairments that are prevalent in disorders like depression and schizophrenia, researchers have focused on the extent to which these individuals 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 alternate sources of motivational impairments, such as an overvaluation of potential negative outcomes for poor performance (e.g., leading 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 effort investment – whether in the classroom or workplace – might be shaped by their past experiences (Bustamante et al., 2021; Grahek, Frömer, et al., 2020; Lieder et al., 2018). For instance, growing up in a volatile environment could downwardly bias 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 puts flesh on these hypotheses (Fig. 2, right), 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, we have recently simulated different ways in which changes in one's mood could theoretically alter their motivation to engage with a task (e.g., by making a task seem easier or harder) (Grahek, Musslick, et al., 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 places a higher premium on performing a difficult task than Participant B (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 different expectations about their likelihood of performing well at the task (Fig. 2A) or places greater weight on avoiding failure (Fig. 2C). This example also assumes that people only ever 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 in spite of it.

The availability of these varied hypotheses also underscores 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 towards addressing such a concern. Because the EVC model is able to ask how performance varies as a function of different model parameters (e.g., expected outcomes vs. expected performance efficacy), we can use it to also ask the same question in reverse: 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, we have quantified how reliably individual differences in a given element of motivation or ability (e.g., the cost of control) can be estimated from their 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 moving outside of the lab to compare a student or professional to their peers. The EVC model lays bare these complexities, and identifies avenues for piecing apart the underlying mechanisms. These avenues further provide opportunities for testing and potentially falsifying the model's core assumptions, and for deepening our understanding of the complexities of control allocation that the model has yet to address. For instance, it remains unknown what the costs are of engaging in the cost-benefit calculation itself, and to what extent those costs encourage people to generate rough approximations to EVC and/or use simplifying heuristics for 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 is necessarily worth it (cf. Bustamante et al., 2021). Addressing this broader set of questions represents a considerable challenge, but one whose benefits will surely outweigh its costs.

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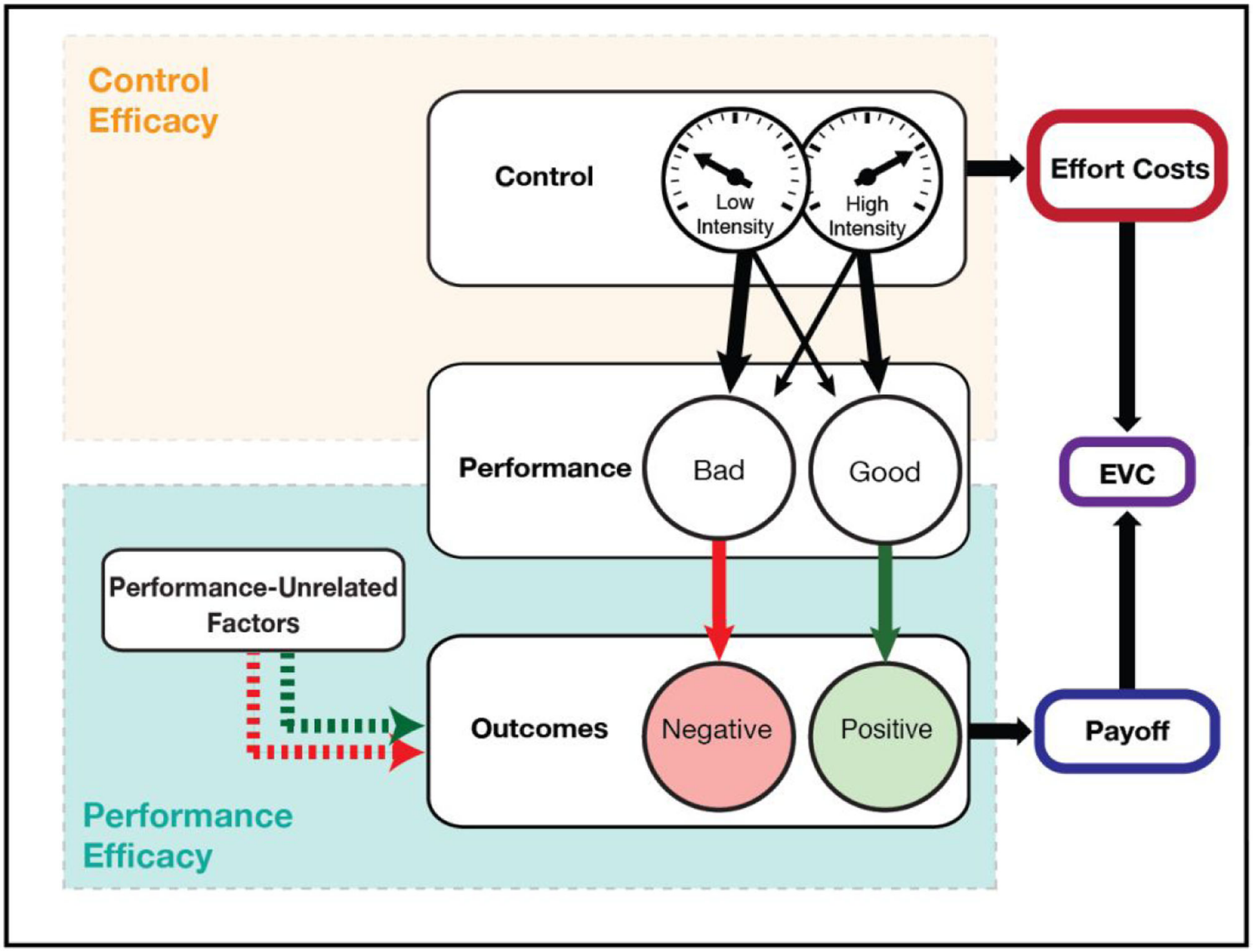

Figure 1.
The Expected Value of Control (EVC) model proposes that we determine how to exert mental effort by weighing the costs and benefits of allocating cognitive control in a particular way given their current situation. Cognitive control is allocated according to two factors: the types of control being engaged (e.g., attention to specific features of a task, suppression of inappropriate responses) and how intensely to engage each of these. The model assumes that we 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). To determine the overall value of a given control allocation (EVC) given the current context, this **effort cost** is weighed against the expected **payoff** for exerting effort. This payoff is determined by the estimated **expected outcomes** for exerting effort (e.g., monetary gain/loss, social approval/admonishment), weighed by the extent to which these outcomes change with increasing control (i.e., effort). The payoff is further determined by whether control *matters* for attaining these outcomes. If greater control has little bearing on one's performance (low **control efficacy**, e.g., if the task is too difficult or is beyond our ability) or if outcomes are expected to be largely determined by performance-unrelated factors like a person's social status (low **performance efficacy**), then control will be deemed less worthwhile. Though not shown here, each of these components can have some

uncertainty around it - for instance, even when outcomes are completely determined by performance, there may be some uncertainty about whether a given outcome will come to pass.

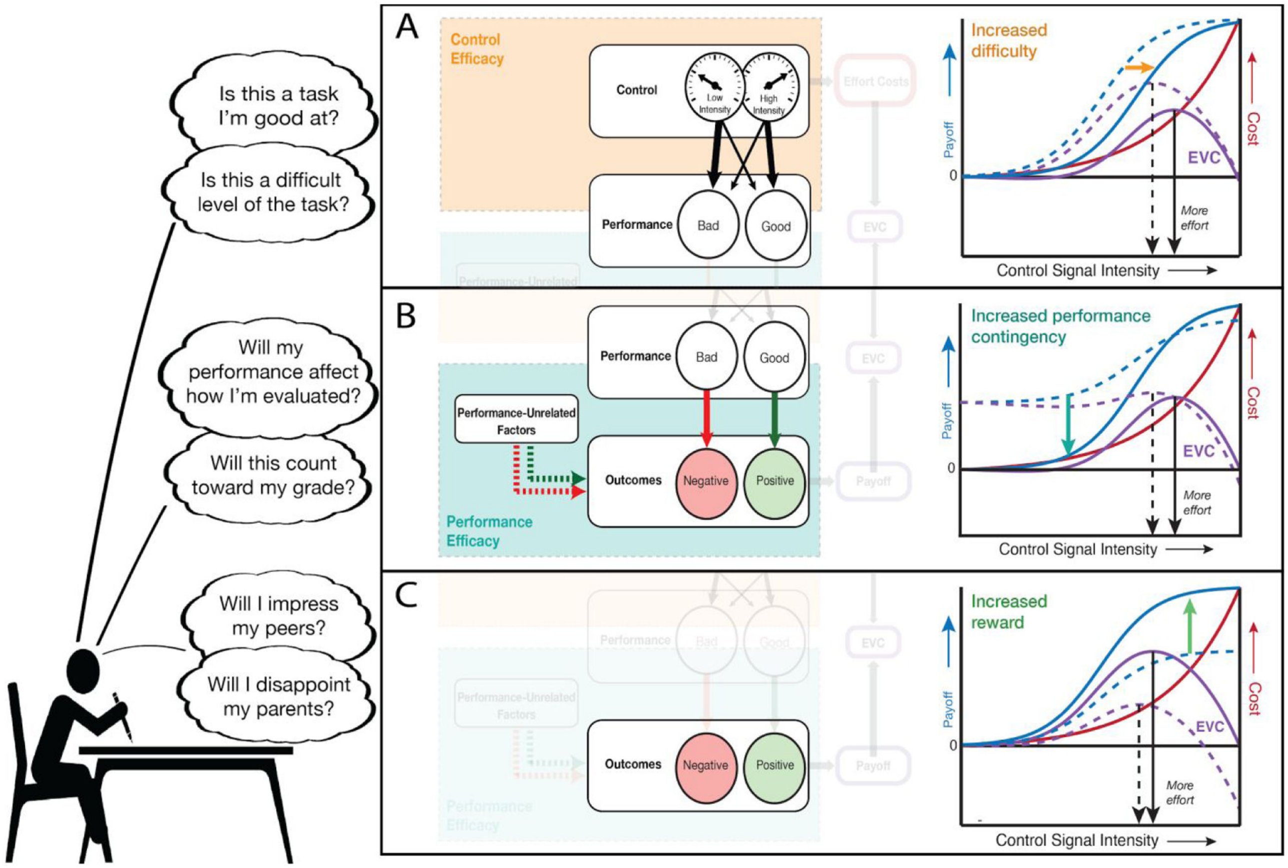

Figure 2.

According to the EVC model, a person's effort allocation (e.g., how hard a student studies for an exam) is jointly determined by what they perceive as their expected outcomes, expected control efficacy, and expected performance efficacy. The student will generally be motivated to invest more effort the more they expect these efforts to achieve positive outcomes and/or avoid negative ones (**C**). However, the motivation to achieve these outcomes will change based on the extent to which the student sees those efforts as an effective means of achieving those outcomes. If the student sees themselves as having little ability to improve their performance by increasing cognitive control (low control efficacy; **A**), or if they perceive their performance as unlikely to be a major factor in determining those outcomes (low performance efficacy; **B**), they will be less motivated to invest effort into the task because the expected payoff for that effort has decreased. On the **right** side of each panel we visualize how changes in each of these components affects the evaluation and allocation of control. For each of these, the EVC for a given control intensity (purple curves) is calculated by subtracting the expected effort costs (red) from the expected payoffs (blue). 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). However, the shape of this payoff curve will vary based, for instance, on expectations of (**A**) task difficulty (affecting how much control is needed to achieve a given level of performance); (**B**) performance contingency (affecting how significantly payoffs increase with increased levels of performance); and (**C**) reward magnitude (affecting how high the peak of the payoff curves at the highest levels of performance). Right panels adapted from Shenhav et al. (2013) and Frömer et al. (2021).