RUNNING HEAD: SELF-CONTROL AS VALUATION

Self-Control as Value-Based Choice

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Abstract

Self-control is often conceived as a battle between “hot” impulsive processes and “cold” deliberative ones. Heeding the angel on one shoulder leads to success; following the demon on the other leads to failure. Self-control *feels* like a duality. What if that sensation is misleading, and, despite how they feel, self-control decisions are just like any other choice? We argue that self-control is a form of *value-based choice* wherein options are assigned a subjective value and a decision is made through a dynamic integration process. We articulate how a value-based choice model of self-control can capture its phenomenology and account for relevant behavioral and neuroscientific data. This conceptualization of self-control links divergent scientific approaches, allows for more robust and precise hypothesis testing, and suggests novel pathways to improve self-control.

Supreme Court Justice Potter Stewart's famous test for obscenity – that he can't define it but "knows it when he sees it" – also applies to self-control. Researchers and laypeople share a set of intuitions about self-control: it feels like being pulled in two directions, it's hard to resolve, and it's critical for attaining desirable outcomes.

We know it when we feel it, but we're barely closer to understanding how it works than we were 2,000 years ago. In *Phaedrus*, Plato compared self-control to a charioteer steering a chariot pulled by two winged horses: one that is noble, rule-bound, and rational, and a second that is unruly, impulsive, and illogical. In Plato's view, self-control is when the charioteer successfully pilots the chariot to a particular destination. The contemporary equivalent of the chariot allegory can be found in dual-process models of control, with one slow, deliberate, and reflective mental process, and a second that is fast, reactive, and impulsive (Kahneman, 2011). The slow process represents long-term goals suggesting one course of action, and it often conflicts with fast, impulsive processes suggesting another (Heatherton & Wagner, 2011; Hofmann, Friese, & Strack, 2009). Self-control is needed when these motives compete, and is typified by overcoming the immediate impulse in favor of the long-term goal.

Consider a dieter deciding between a salad or burger for lunch. One option promotes a long-term weight loss goal, the other satisfies an immediate hedonic urge. Dual-system models typically assume that the urge is automatic and must be effortfully inhibited or overcome to promote the goal. But there are many different routes to choosing the salad, only some of which involve effortful inhibition (Fujita, 2011). The dieter could increase the appeal of the salad by noticing the tasty tomatoes on top, focusing on the satisfaction of making progress toward a cherished goal, or considering the approval earned by living up to social expectations. There are also numerous situational strategies that could have eliminated the temptation before it arose, such as choosing a restaurant that offers only healthy choices (Duckworth, Gendler, & Gross, 2016). Dual-process models collapse this universe of behaviors into a single process, inhibition, and in so doing, ignore the diversity of pathways to self-control success (Keren & Schul, 2009).

Here, we put forward a radical thesis: there is nothing unique about self-control. Instead, decisions that we label self-control are merely a fuzzy subset of all value-based decisions, which involve selecting a course of action among several alternatives. These decisions feel hard and are often characterized by tradeoffs between short- and long-term rewards (Duckworth et al., 2016). Society treats self-control decisions as special because they are central to goal pursuit, but doing this might inadvertently reify a concept that does little to advance knowledge. Here, we describe the advantages of recasting self-control as no more and no less than value-based decision-making.

The Model: Self-Control as Value-Based Choice

Value-based decision-making involves selecting from a set of options based on their relative subjective value. How does this process describe self-control? We define self-control as the process of selecting a behavior that is consistent with a focal goal when it conflicts with goal-inconsistent alternatives. This process involves calculating a value for each option by integrating various gains (e.g., money, social approval) and costs (e.g., effort, opportunity costs), transforming objective to subjective value in predictable ways (e.g., discounting delayed rewards, penalizing effort), and enacting the most valued option. Attention plays a crucial role in adaptive choice and self-control by gating which options enter the choice set at any one moment and foregrounding their salient attributes. Individual differences in cognitive and attentional control may influence self-control through their effect on the choice set, but executive functions do not necessarily have a one-to-one relationship with self-control. For example, though they are related (Hofmann, Schmeichel, & Baddeley, 2012), self-control is not always reducible to effortful inhibition (e.g., Fujita, 2011; Milyavskaya & Inzlicht, in press).

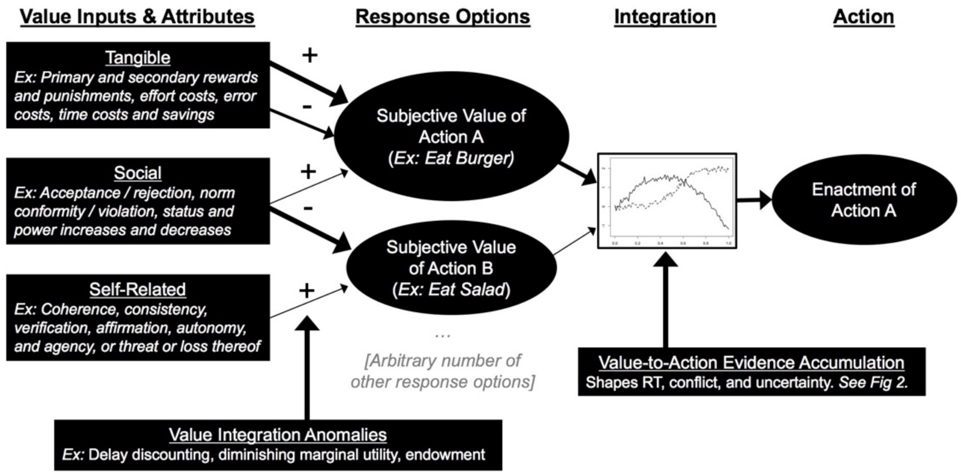
Value-based choice is characterized at several levels, which enables it to bridge multiple ways of understanding self-control. Following the insight that mental systems can be understood at interrelated levels of analysis (Marr & Poggio, 1976), we describe how value-based choice accounts for self-control at the computational, neural, and phenomenological levels.

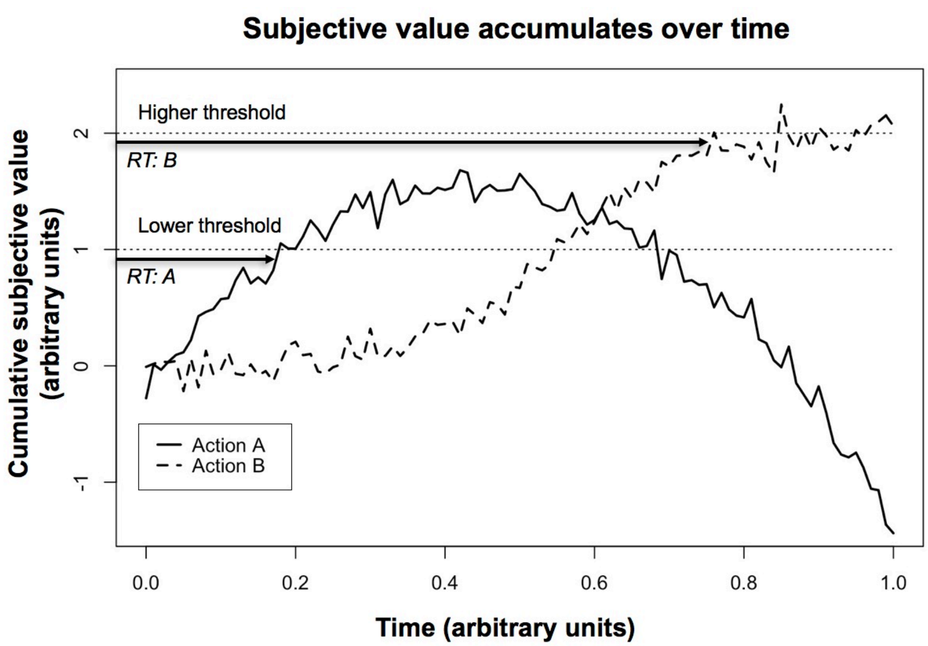
Computation

Our recent work demonstrates that a simple, algorithmically precise, neurobiologically-inspired computational model of value-based choice is capable of capturing several aspects of self-control choices (Hutcherson, Bushong, & Rangel, 2015a), including why they vary with time/time pressure, as described below. This model has two key features. First, it builds on extensive work in economics and psychology that describes the subjective value of an option as the weighted sum of choice-relevant attribute values:

$$SV = \Sigma_i w_i Attribute_i.$$

These weights can vary by person, context, and time (Figure 1). Second, it assumes that neurons track subjective value in a *noisy, probabilistic* fashion, perhaps due to attentional fluctuations or the inherent stochasticity and oscillatory nature of neuronal firing (Busemeyer & Townsend, 1993). To reduce the impact of noise on choice, the model takes the fluctuating signals as *evidence* for or against a particular choice, accumulating them over time until the *accumulated evidence* passes a threshold for committing to a decision (Figure 2). Higher thresholds maximize accuracy, and lower thresholds maximize response speed. Models of this sort (called *drift diffusion models* or *sequential accumulation models)* capture choice and response time patterns with remarkable accuracy across various value-based, perceptual, and memory-based decisions (Ratcliff & Frank, 2012).





This model has several implications for self-control. First, how long a choice takes depends not on whether a “control” system is active, but on the threshold and subjective value of the options. Weaker subjective values and higher thresholds produce longer decision times because evidence accumulates more slowly and more evidence is needed for a decision (Hutcherson et al., 2015a). Second, the model is stochastic. Choices can vary from one time to the next simply due to noise rather than the occasional engagement of control. Third, the model captures overt behaviors (e.g., food choice) and also decisions about internal events (e.g., effort expenditure) by incorporating both internal and external attributes into the value-integration process. Finally, the model is dynamic and iterative: the accumulated evidence is sensitive to changes in value signals, explaining changes of mind when new evidence becomes available (e.g., Resulaj, Kiani, Wolpert, & Shadlen, 2009), when attention shifts (e.g., Krajbich, Armel, & Rangel, 2010), or when construal or framing changes (Kahneman & Tversky, 1984).

Neural implementation

Neurobiological research on self-control initially appeared to support dual-system models. For example, self-controlled choices corresponded to more activity in lateral prefrontal areas and less activity in areas associated with reward, including ventral striatum and ventromedial prefrontal cortex (McClure et al., 2004). However, evidence that regions previously thought to be involved only in automatic reward responses can instead reflect the value of both controlled and impulsive choices questioned this interpretation (Kable & Glimcher, 2007). This result suggests a value integration process captured by the computational model outlined above rather than an inhibitory relationship between two processes.

Activity in different brain areas tracks the value of distinct attributes, including gains and losses (Basten, Biele, Heekeren, & Fiebach, 2010), emotional and utilitarian benefits of moral actions (Hutcherson, Montaser-Kouhsari, Woodward, & Rangel, 2015b), an option’s value for self and others (Hutcherson et al. 2015a), and the value of waiting for a better outcome (McGuire & Kable, 2015). These attribute-specific representations *converge* in areas like the ventral striatum, ventromedial prefrontal and orbitofrontal cortices, whose activity correlates with the *overall* subjective value of an option (Clithero & Rangel, 2014). Moreover, electrophysiological recordings show patterns of neural response in several areas (including ventromedial prefrontal cortex) consistent with the kind of accumulation-to-threshold signals implied by the model (Strait, Blanchard, & Hayden, 2014).

This architecture suggests that self-control operates as a valuation process rather than a battle between different systems. Dual-system models generally postulate that systems representing long-term attributes and hedonic considerations compete to inhibit each other, with the winner driving behavior. Yet neural evidence for this kind of reciprocal inhibition is scarce (Hutcherson et al., 2015b; Kelley, Wagner, & Heatherton, 2015). In contrast, value signals in regions like the vmPFC track choices *regardless* of whether that choice is patient or impatient, healthy or unhealthy, charitable or selfish. Self-control outcomes are determined by the relative degree to which the value of *all* attributes are reflected in vmPFC (Kable & Glimcher, 2007; Hutcherson et al., 2015a). Control networks such as lateral prefrontal cortex contribute to self-control by influencing the weights given to different attributes in the value integration process, rather than by inhibiting other regions (Hare, Malmaud, & Rangel, 2011). Thus, self-control outcomes emerge organically from the operation of a single, integrative system with input from multiple regions rather than antagonistic competition between two processes.

Phenomenology

Self-control feels hard, aversive, and draining (Inzlicht, Bartholow, & Hirsh, 2015). This sense of effort and conflict contributes to self-control decisions seeming different from other kinds of choice, like a battle in which a short-sighted id must be conquered by a virtuous ego. Yet, the experience of conflict does not guarantee that two mental systems are in fact battling for dominance (Keren & Schul, 2009). A value-based choice model can account for the characteristic sensations of duality and effort in self-control.

Self-control decisions are frequently morally tinged, with one choice being socially-sanctioned and good and the other shameful and bad. Moral overtones could contribute to feelings of conflict: as people's attention alternates between these charged options, their value fluctuates too, gravitating toward the presently-attended option (Krajbich et al., 2010). Attention-driven fluctuations in value during choice may generate feelings of conflict or uncertainty (Kiani, Corthell, & Shadlen, 2014).

Despite its phenomenology, self-control does not actually deplete a physical resource (Inzlicht & Berkman, 2015; Marcora, 2009). Instead, effort can be construed as one of many subjectively-constructed attributes (Dunn, Lutes, & Risko, 2016) that determine value. Effort might reflect an opportunity cost (Kurzban, Duckworth, Kable, & Myers, 2013), signaling the benefit of focusing on other, more valued tasks. Thus, effort might partly indicate the relative priority of the current activity; high-priority tasks have low opportunity costs because alternatives are less important. This may be why shifting from something dull or unimportant to something exciting or important can feel rejuvenating, even after a period of exertion (Inzlicht, Schmeichel, & Macrae, 2014). Effort might also signal that a task is error-prone and thus something to be avoided (Dunn, Inzlicht, & Risko, 2017).

The notion of effort-as-cost has also been noted in decision-making and neuroscientific studies. The value of certain mental activities (e.g., attentional control) is discounted because they feel effortful, even when they are deemed important (Westbrook & Braver, 2015). That is, even when they are high-priority, tasks that rely on cognitive processes with strict parallel processing limits might feel hard because they pose opportunity costs and increase error likelihood (Dunn et al., 2016, Inzlicht et al., 2015; Shenhav et al., in press). People who characteristically treat effort as costly avoid it, and are also poor at self-control (Kool, McGuire, Wang, & Botvinick, 2013). The dorsal anterior cingulate cortex (dACC), implicated in control, also seems to calculate the return-on-investment of the effort required by a task, promoting efficient allocation of mental resources (Shenhav, Cohen, & Botvinick, 2016).

In sum, the cost of engaging in self-control is represented in the brain, weighted against the benefits, and dynamically integrated into decisions alongside other considerations (e.g., Boureau, Sokol-Hessner, & Daw, 2015). These results underscore the deeper point that the phenomenology of self-control (duality, effort) may follow from properties of the decision-making process (attention shifts, cost) rather than indicate the presence of dual-competitive processes.

Implications and Future Directions

Viewing self-control as a decision reveals novel predictions based on insights from decision science. That field has identified a variety of choice "anomalies" (Kahneman, Knetsch, & Thaler, 1991), such as the tendency to undervalue delayed gains (*temporal discounting*) and to overvalue items one possesses (*endowment effect*). These choice anomalies may apply to self-control, providing new ways to understand and intervene on self-control. For instance, self-control is hypothesized to be more likely if the goal is perceived as temporally closer or feels "owned" by the pursuer. Other predictions pit valuation and dual-process accounts against each other. For example, when a person with a "cold" dieting goal is tempted by a "hot" unhealthy snack, dual-process models focus on the strength of the hot process and the fatigue of the cold one. But this ignores fluctuations in the goal's value from choice anomalies and other dynamic processes, such as when framing alters an option's salient attributes (Duckworth et al., 2016).

Value-based choice inspires new research questions. One concerns neural implementation. Knowledge is rapidly accumulating about the role of the vmPFC in value integration and the dACC in effort costs, but how those two regions interface during self-control is unknown. It is also currently unclear how and why damage to key regions can make choices more impulsive.

Other questions relate to the number and nature of the sources of value. Choice attributes and their weights can change dynamically, explaining variations in choice within and across individuals. The variety of possible attributes gives the valuation model more nuance than alternatives, but this flexibility also presents a challenge to explaining and predicting behavior a priori. Given a person in a situation, can all value inputs to a choice be known? A systematic taxonomy of value sources will be needed to answer this question. Executive functions such as cognitive and inhibitory control can influence the valuation process (e.g., Hare et al., 2011), but when and how they do remains unknown.

Finally, this model poses questions about improving self-control. Theoretically, re-weighting the value inputs during choice could improve self-control. If some attributes (e.g., healthiness) are linked to goal attainment, then interventions that increase those attributes' weights should increase self-control. For example, autonomously motivated goals hold elevated subjective value (Deci & Ryan, 2000). How can autonomous motivation be increased? Can training reliably increase the salience and weight of goal-promoting attributes? And how does intervention work in multiple-goal situations where advancing one goal might detract from others (e.g., health and relational goals)?

Conclusion

We propose that self-control is simply a form of value-based decision-making. This recasting provides a parsimonious framework that bridges research areas and explains the phenomenon at several interrelated levels. A value-based choice explanation of self-control also opens lines of inquiry that would not otherwise be apparent.

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Recommended Readings

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science*, *324*(5927), 646–648.
One of the first papers to demonstrate the role of the vmPFC in self-control. Provides evidence that lateral prefrontal regions influence self-control by modulating an integrated value signal rather than by inhibiting subcortical emotion or reward regions.

Hutcherson, C., Bushong, B., & Rangel, A. (2015). A neurocomputational model of altruistic choice and its implications. *Neuron, 87*(2), 451-462.
Develops a computational model of altruism that accurately predicts choice, response time, and neural activity. The model suggests that many patterns of data interpreted as evidence for dual-process (e.g., intuitive versus deliberative) systems, including RT, response to time pressure, and neural response, can be explained by a simpler value computation.

Polanía, R., Krajbich, I., Grueschow, M., & Ruff, C. C. (2014). Neural oscillations and synchronization differentially support evidence accumulation in perceptual and value-based decision making. *Neuron*, *82*(3), 709–720.
An empirical article illustrating how brain activity (measured here with electroencephalography) can be characterized using evidence accumulator models. The paper also shows how different types of choices (e.g., perceptual versus value-based) integrate different sources of evidence.

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281.
An accessible overview of a variety of sequential sampling models, including drift-diffusion models, that describes their features, compares them to each other, and reviews how they have been used in psychological research.

Shenhav, A., Musslick, S., Lieder, F., Kool, W., Griffiths, T. L., Cohen, J. D., & Botvinick, M. M. (in press). Toward a rational and mechanistic account of mental effort. *Annual Review of Neuroscience*.
A detailed review of the psychological and neuroscientific literatures on the experienced effort costs of cognitive control. Summarizes potential causes of effort costs, such as opportunity costs, and storage and processing limits, and describes computational models of effort allocation.

Figure Captions

Figure 1. Value-based choice model of self-control. The cumulative subjective value of each each response option (middle column) is a weighted sum of value inputs based on the option's attributes (left column). Example attributes for a choice option include primary rewards, effort costs, social acceptance or rejection, and self-consistency and -verification. The subjective value integration is not strictly rational, but instead is modulated by a number of choice "anomalies" such as the tendency to discount delayed gains. Value accumulates dynamically and stochastically across time until a threshold is reached, and attention can influence the accumulation process by altering the relevant attributes. The option with the greatest value when the threshold is reached or time runs out is enacted.

Figure 2. Value accumulation across time for two hypothetical choice options. Action A (solid line) accumulates subjective value rapidly then drops off, whereas Action B (dashed line) accumulates value more slowly but it eventually reaches a greater value. These temporal dynamics could occur either due to randomly-accumulated fluctuations, or due to systematic differences in the nature of A and B (e.g., more abstract versus more concrete attributes). In either case, Action A would tend to be selected (and more quickly) if a low decision threshold were used because it reaches the threshold first, but Action B would be selected (and more slowly) if a higher decision threshold were set. The selected action also depends on the time available for the decision: Action A would tend to be selected if a short limit were imposed. Also, the noise depicted in the lines indicates stochasticity in the valuation process: repetitions of the same choice might result in selection of Action B occasionally, even in a short response window, due to random variation; for the same reason, Action A would sometimes be selected in a long response window.