



Neural and Computational Mechanisms of Motivation and Decision-making

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Abstract

■ Motivation is often thought to enhance adaptive decision-making by biasing actions toward rewards and away from punishment. Emerging evidence, however, points to a more nuanced view whereby motivation can both enhance and impair different aspects of decision-making. Model-based approaches have gained prominence over the past decade for developing more precise mechanistic explanations for how incentives impact goal-directed behavior. In this Special Focus, we highlight three studies that demonstrate how computational frameworks help decompose decision processes into constituent cognitive components, as well as formalize

when and how motivational factors (e.g., monetary rewards) influence specific cognitive processes, decision-making strategies, and self-report measures. Finally, I conclude with a provocative suggestion based on recent advances in the field: that organisms do not merely seek to maximize the expected value of extrinsic incentives. Instead, they may be optimizing decision-making to achieve a desired internal state (e.g., homeostasis, effort, affect). Future investigation into such internal processes will be a fruitful endeavor for unlocking the cognitive, computational, and neural mechanisms of motivated decision-making. ■

BACKGROUND

Over the past decade, a plethora of studies have examined interactions between motivation and goal-directed decision-making, which often recruits the process of cognitive control (Cubillo, Makwana, & Hare, 2019; Yee & Braver, 2018; Kool et al., 2017; Krebs & Woldorff, 2017; Chiew, Stanek, & Adcock, 2016; Fröber & Dreisbach, 2016; Botvinick & Braver, 2015; Braem, Hickey, Duthoo, & Notebaert, 2014; Braver et al., 2014; Dixon & Christoff, 2012; Padmala & Pessoa, 2010; Pessoa, 2009; Engelmann & Pessoa, 2007). This research has been highly influential for cognitive neuroscience, shedding light on variability in underlying cognitive and neural mechanisms of these interactions across the human lifespan (Insel, Charifson, & Somerville, 2019; Davidow, Insel, & Somerville, 2018; Ferdinand & Czernochowski, 2018; Samanez-Larkin & Knutson, 2015; Luna, Paulsen, Padmanabhan, & Geier, 2013) as well as in psychiatric and neurological disorders (Barch et al., 2023; Grahek, Shenhav, Musslick, Krebs, & Koster, 2019; Timmer, Aarts, Esselink, & Cools, 2018; Rosa, Schiff, Cagnolati, & Mapelli, 2015).

Researchers have leveraged powerful neuroimaging, electrophysiological, and pharmacological tools to uncover key neural signatures of motivational influences on control allocation. For instance, numerous fMRI studies reveal a consistent network of regions across prefrontal and mid-cingulate cortex related to the interaction

between motivation and cognitive control (Yee, Crawford, Lamichhane, & Braver, 2021; Parro, Dixon, & Christoff, 2018; Bahlmann, Aarts, & D'Esposito, 2015; McGuire & Botvinick, 2010; Kounieher, Charron, & Koechlin, 2009; Bush et al., 2002). Similarly, multiple EEG studies have identified various ERP components (e.g., P3a, P3b, CNV, FRN) modulated by reward and cognitive control (Grahek, Frömer, Fahey, & Shenhav, 2023; Overmeyer, Kirschner, Fischer, & Endrass, 2023; Fröber, Jurczyk, Mendl, & Dreisbach, 2021; Frömer, Lin, Wolf, Inzlicht, & Shenhav, 2021; Schevernels, Krebs, Santens, Woldorff, & Boehler, 2014), and recent intracranial EEG studies suggest that beta and theta oscillations may be involved in tracking reward learning and effort allocation (Xiao et al., 2024; Hoy et al., 2024). Finally, pharmacological and neurochemical PET studies have shown how striatal dopamine potentiates the sensitivity to the benefits (relative to the costs) of subjective effort, which subsequently biases the allocation of cognitive control (Westbrook et al., 2020; Cools et al., 2019; Cools, 2016).

However, despite the emerging evidence for the neural substrates underlying these motivation–cognition interactions, a significant limitation of cognitive neuroscience approaches is that measurement of neural activity alone does not necessarily specify how motivational value signals are represented—and subsequently translated—into strategic adjustments in cognitive control and goal-directed decision-making. Crucially, the inclusion of computational models, in conjunction with carefully designed experimental tasks and neural measurements, allow

researchers to characterize how value information is represented. In this Special Focus, we highlight how computational models allow for a greater insight into the mechanisms through which motivational and cognitive processes interact to bias adaptive goal-directed behavior.

ADVANCES FROM COMPUTATIONAL COGNITIVE NEUROSCIENCE: THE CASE FOR PROCESS MODELS

In recent years, the rise of computational cognitive neuroscience has transformed the field of reward and decision-making, fostering an innovative interdisciplinary approach for formally characterizing various motivational, affective, and cognitive processes in humans and animals (Kriegeskorte & Douglas, 2018; Forstmann & Wagenmakers, 2015; O'Doherty, Hampton, & Kim, 2007). Computational frameworks are especially powerful tools to test various normative assumptions about cognitive control and decision-making (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Botvinick, Braver, Barch, Carter, & Cohen, 2001; Braver & Cohen, 2000), and recent advances have illustrated how humans may adopt behavioral control strategies to maximize expected value (Prater Fahey, Yee, Leng, Tarlow, & Shenhav, 2025; Silvestrini, Musslick, Berry, & Vassena, 2023; Leng, Yee, Ritz, & Shenhav, 2021; Shenhav, Prater Fahey, & Grahek, 2021; Shenhav et al., 2017; Musslick, Shenhav, Botvinick, & Cohen, 2015; Shenhav, Botvinick, & Cohen, 2013).

Several of these normative assumptions have been implemented via sequential sampling models (SSMs) and reinforcement learning models (Fengler, Bera, Pedersen, & Frank, 2022; Ratcliff, Smith, Brown, & McKoon, 2016; Forstmann, Ratcliff, & Wagenmakers, 2015; Forstmann & Wagenmakers, 2015; Wiecki, Poland, & Frank, 2015; Wiecki, Sofer, & Frank, 2013), process models that decompose task performance (e.g., RT, accuracy) into mathematical parameters related to underlying psychological processes of value-based decisions. For example, in a SSM, the drift rate may represent the quality of information processing, whereas the decision threshold may represent the level response caution an individual may choose to exert.

Model-based approaches have generated important insight into how particular decision-making processes are implemented in specific brain areas or via specific neural signals (Rac-Lubashevsky & Frank, 2021; Collins, Ciullo, Frank, & Badre, 2017; Herz, Zavala, Bogacz, & Brown, 2016; Frank et al., 2015; Niv et al., 2015; Ahn, Krawitz, Kim, Busemeyer, & Brown, 2011; Cavanagh et al., 2011; Daw, Gershman, Seymour, Dayan, & Dolan, 2011; O'Doherty et al., 2007). For example, Rac-Lubashevsky and Frank (2021) conducted an EEG study to examine the neural dynamics of selective gating operations in working memory (e.g., input gating, response gating, and output gating). They identified various neural markers associated with the three gating effects (e.g., input gating is associated with increased in parietal P3b,

output switching is associated with negative enhancement of N2), and they find evidence for trial-wise neural similarity following switches in the input, output, and response gates across various ERP components. Next, they used a drift diffusion model (a kind of SSM) and tested the hypothesis that premotor conflict would increase “decision threshold,” a parameter associated with more cautious and deliberate response selection. They found that switches at each independent level of gating (input, output, and response) were related to increased decision thresholds, consistent with prior work demonstrating that the basal ganglia neural systems are associated with the impact of decision-conflict and associated adjustments decision threshold (Wiecki & Frank, 2013; Cavanagh et al., 2011). Together, these data reveal the neural and computational markers of how information is gated in working memory.

It is also worth mentioning that although model-based approaches are incredibly powerful, they are not immune to misinterpretation of neural mechanisms if not implemented carefully (Frömer, Nassar, Ehinger, & Shenhav, 2024). Therefore, greater rigor is necessary to determine the validity and reliability of computational models fit to behavioral and neural data. In recent years, researchers have sought to develop robust analysis pipelines and workflows for systematically evaluating the quality of model fitting and validation (e.g., posterior predictive checks), which will determine to what extent such model-based approaches can provide meaningful insight into cognitive and neural mechanisms of value-based decisions (Schad, Betancourt, & Vasishth, 2021; Gelman et al., 2020; Pedersen & Frank, 2020; Wilson & Collins, 2019; Wilson & Niv, 2015).

COMPUTATIONAL MODELS REVEAL HOW MOTIVATION CAN BOTH ENHANCE AND IMPAIR GOAL-DIRECTED DECISION-MAKING

Motivation shapes adaptive decision-making by biasing action toward reward and away from punishment (Swart et al., 2017; Guitart-Masip, Duzel, Dolan, & Dayan, 2014). Yet, recent research suggests that motivation may play a more nuanced role in both enhancing and impairing goal-directed decision-making (Yee, Leng, Shenhav, & Braver, 2022; Millner, Gershman, & Nock, 2018; Pessiglione & Delgado, 2015). The three empirical features in this Special Focus—that accompany this perspective—illustrate how computational modeling can be leveraged to formalize when and how motivational incentives impact decision-making. The following collection of studies reveals how motivation plays a multifaceted role in goal-directed decision-making.

First, Adkins and Lee (2023) use an innovative forced-response paradigm and complementary model to examine the effects of incentives on the preparation of goal-directed and habitual responses in a Simon task. In this task, response initiation time was fixed but the onset of a target stimulus varied between trials, thereby limiting

how much time was available for response preparation (Hardwick, Forrence, Krakauer, & Haith, 2019). Using a probabilistic model that separately parameterizes the speed of habit and goal processing (mean = μ , $SD = \sigma$), they demonstrate that monetary rewards mitigate conflict by accelerating the preparation of goal-directed actions. Importantly, the inclusion of the computational model provided a uniquely powerful approach for generating explicit predictions that differentiate between two distinct hypotheses for how rewards impact cognitive strategies in this cognitive control task (i.e., enhanced goal-directed response preparation vs. impaired habitual response).

Second, Ballard, Waskom, Nix, and D'Esposito (2024) examine whether reward reinforcement can give rise to habitual goal selection (e.g., using contextual information to habitually select a specific stimulus–response rule), using a novel rewarded context-dependent, perceptual decision-making task. Whereas prior work has shown that rewards promote habitual action selection (e.g., automatic response to a specific stimulus), the authors reveal that rewards also reinforce abstract representations of task goals to adaptively guide action selection and, additionally, that learned associations persist even when rewards are no longer present. Using drift diffusion modeling, a specific type of SSM, they characterize the key qualitative features of the behavioral data (i.e., rewards promoted faster and more accurate responding for more difficult trials), which was reflected in greater efficiency of evidence accumulation (drift rate), higher response caution (decision threshold), as well as slower initiation times (nondecision time). Here, the drift diffusion model provided additional insight into the underlying mechanisms of the decision-making process, allowing for a more nuanced understanding of the role of reward incentives in enhancing versus impairing habitual goal selection.

Third, Zhang, Leng, and Shenhav (2024) investigate whether and how reward incentives interact with an expected challenge—which is inherently stressful—to determine cognitive control allocation. They develop a time-limited incentivized Stroop task requiring individuals to meet a goal threshold (number of correct trials) to receive accumulated monetary reward, and vary the goal threshold (i.e., “Easy” challenge level required only five correct responses to reach the goal, whereas the “Hard” challenge level required eight correct responses to reach the goal) and rewards at stake (i.e., the “Low” reward is equivalent to one gem, whereas the “High” reward is equivalent to multiple gems). In other words, the goal threshold determines the difficulty of a given interval. They observe an interesting behavioral pattern in which individuals invested a greater effort for higher rewards and greater challenge, consistent with model predictions from a reward rate optimization model, which assumes that reward promotes more efficient performance (Leng et al., 2021). Interestingly, despite both conditions improving overall task performance, each influenced divergent affective states, with greater reward associated with higher

stress and higher positive affect versus greater challenge associated with higher stress and lower positive affect, and these affective ratings interacted with whether the goal was completed. Finally, analyses of temporal dynamics across task intervals reveal initial speeding at the start of an interval and more caution closer to goal completion, suggesting dynamic reconfigurations of control across information processing (Grahek et al., 2024; Ritz, Leng, & Shenhav, 2022). Together, these studies reveal an intriguing dissociation between how various motivational manipulations (reward vs. challenge) can similarly bias cognitive control yet contribute to dissociable affective experiences.

BEYOND MONETARY INCENTIVES: CONSIDERING THE NORMATIVE ROLE OF HOMEOSTASIS, EFFORT, AND AFFECT IN DECISION-MAKING

This collection highlights how computational modeling can provide a unique perspective into mechanisms that determine when and how motivational incentives can bias distinct components of decision-making processes in well-defined cognitive tasks. Yet, although these studies demonstrate the power of monetary incentives in guiding adaptive behavior in the service of a goal, it remains unclear to what extent these incentives are sufficient to modulate more complex decision-making processes. Alternatively, what happens when rewards or goals are delayed in time or more abstract?

A central assumption of many current influential models of reward and decision-making is that individuals behave to maximize expected (monetary) value, yet in the real world, we know that humans are motivated by a wide array of reinforcers (Krug & Braver, 2014; Bartra, McGuire, & Kable, 2013; Sescousse, Caldú, Segura, & Dreher, 2013). Although it is well known that extrinsic incentives or secondary reinforcers (e.g., money, food/drink, social interactions) serve as rewards that bias internal states (e.g., homeostatic drive, motives) to support adaptive goal-directed behavior (Molinero & Collins, 2023; O'Reilly, 2020; Juechems & Summerfield, 2019), another puzzling phenomenon is that humans and animals often behave in a manner that some normative models would consider “suboptimal” (Adkins, Lewis, & Lee, 2022; Farashahi, Donahue, Hayden, Lee, & Solanti, 2019; Rouault, Drugowitsch, & Koechlin, 2019; Herrnstein, 1997; Kahneman & Tversky, 1979). That is, precisely what humans and animals are optimizing their behavior for when faced with extrinsic rewards remains unclear (Cohen & Blum, 2002). Below, I briefly describe three recent developments that may provide insight into this open question.

One provocative idea that has gained traction in recent years is that humans and animals adaptively learn about and seek “rewards” to regulate internal homeostasis of the organism (Keramati & Gutkin, 2014). Although the distinction between homeostatic and hedonic mechanisms

in decision-making is well known (Saper, Chou, & Elmquist, 2002), how peripheral and central nervous systems interact to control adaptive decision-making and influence behavior remains an active area of research (Rossi & Stuber, 2018; de Araujo, Schatzker, & Small, 2020; Lutter & Nestler, 2009). For example, recent evidence from the ingestive literature has identified the postoral “primary reward signal” in the body as an interoceptive signal that represents key physiological resources essential for sustaining life, such as energy, nutrients, and hydration (Weber, Yee, Small, & Petzschnner, 2024). Importantly, these primary reward signals depend on an organism’s internal state (e.g., hunger, thirst) as well as its goals (e.g., satiety, quenching thirst), providing a potential explanation that may help reconcile the paradoxical and subjective nature of food and drink rewards (e.g., a drop of juice may be appetitive if an animal is thirsty, yet aversive if the animal is quenched). Neurocomputational frameworks that simultaneously consider homeostatic-based and reward-based mechanisms between the body and brain may facilitate a comprehensive understanding of how rewards bias adaptive decision-making (Plassmann, Schelski, Simon, & Koban, 2022; Petzschnner, Garfinkel, Paulus, Koch, & Khalsa, 2021; Juechems & Summerfield, 2019; Hulme, Morville, & Gutkin, 2019; Paulus, 2007).

Second, an emerging body of research has shown that individuals seek to minimize the cost associated with exerting mental (or cognitive) effort in decision-making tasks (Kool & Botvnick, 2018; Shenhav et al., 2017; Westbrook & Braver 2015). Although it is well established that mental effort is phenomenologically aversive and that humans and animals typically seek to avoid exerting effort because of its subjective internal cost (Vogel et al., 2020; Kurzban, 2016), the precise mechanism underlying the effort cost remains elusive. Recent computational frameworks have sought to quantify effort as a cost–benefit analysis between reward and effort (Manohar et al., 2015), or as an opportunity cost (Otto & Daw, 2019). However, as “effort” is entirely subjective and intrinsic, a limitation of current empirical studies is that effort has been primarily manipulated by varying the magnitude of an extrinsic motivational incentive (e.g., monetary reward or loss). Moreover, an intriguing challenge of quantifying effort relates to its paradoxical nature in either adding to or subtracting from value depending on an organism’s level of effort exertion (Inzlicht, Shenhav, & Olivola, 2018). Future work clarifying the computational mechanisms of *when* organisms exert mental effort as well *how* they experience it can provide insight into an important latent factor of adaptive decision-making.

Finally, growing evidence suggests that affect, in addition to reward, plays a prominent role in driving cognition and behavior (Schiller et al., 2024; Dukes et al., 2021; Lerner, Li, Valdesolo, & Kassam, 2015; Paulus & Yu, 2012). Researchers have shown dissociable influences of affect versus reward on cognitive control (Chiew, 2021; Grahek, Musslick, & Shenhav, 2020; Fröber & Dreisbach,

2014; Harlé, Shenoy, & Paulus, 2013; Chiew & Braver, 2011), and in this Special Focus, Zhang and colleagues demonstrate how different motivational influences that similarly improve performance can lead to distinct affective states. This notion that an organism’s internal state determines the perception of the external rewarding stimulus is not new (Cabanac, 1971), and recent computational frameworks posit that humans make decisions in the service of their emotional and affective states (Shenhav, 2024; Emanuel & Eldar, 2023; Dayan, 2022). Importantly, these models assume that organisms act in accordance with their affective goals, which may help provide normative assumptions for when and how humans behave rationally (e.g., in the service of optimizing mood).

Conclusion

In conclusion, these recent developments suggest a necessary shift from the assumption that “motivation” is always implicitly manipulated in humans and animals through offering extrinsic incentives such as monetary rewards. Instead, given that motivation is an internal state that interacts with the physiological and psychological needs of the organism, it seems natural the computational models should account for neural/bodily signals, subjective effort costs, and internal affective states when describing the impact of motivation and adaptive goal-directed behavior. Such computational frameworks that formalize interactions between motivation, affect, and decision-making would enable a richer understanding of the multifaceted ways through which motivation and decision-making processes interact both in the laboratory and in the real world. Clarification of these interactions could lend crucial insight into how these mechanisms may become maladaptive in psychiatric disorders (Bishop & Gagne, 2018; Pessiglione, Vinckier, Bouret, Daunizeau, & Le Bouc, 2018), laying the groundwork for more effective translation from computation to the clinic (Yip et al., 2022).

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Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience (JoCN)* during this period were $M(\text{an})/M = .407$, $W(\text{oman})/M = .32$, $M/W = .115$, and $W/W = .159$, the comparable proportions for the articles that these authorship teams cited were $M/M = .549$, $W/M = .257$, $M/W = .109$, and $W/W = .085$ (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance. The authors of this paper report its proportions of citations by gender category to be: $M/M = .531$; $W/M = .208$; $M/W = .125$; $W/W = .135$.

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