CHAPTER 2

Instrumental Divergence and Goal-Directed Choice

Mimi Liljeholm
Cognitive Sciences, University of California, Irvine, Irvine, CA, United States

INTRODUCTION

An essential aspect of flexible choice is that alternative actions yield distinct consequences: If all available actions have identical, or highly similar, outcome distributions, such that selecting one action over another does not significantly alter the probability of any given outcome state, an agent's ability to exert control over its environment is considerably impaired. Conversely, when alternative actions produce distinct outcome states, discrimination and selection between actions allow an agent to flexibly obtain the currently most desired outcome. Since subjective outcome utilities are constantly changing, such flexible control is essential for reward maximization and, thus, may have intrinsic value, serving to motivate and reinforce specific decisions, as well as to generally justify the processing cost of goal-directed computations. In this chapter, I discuss work investigating the role of *instrumental divergence*—the degree to which actions differ with respect to their outcome probability distributions—in goal-directed choice.

Formal theories of goal-directed decisions postulate that the agent generates a "cognitive map" of stochastic relationships between actions and states such that, for each action in a given state, a probability distribution is specified over possible outcome states. These transition probabilities are then combined with current estimates of outcome utilities in order to generate action values—the basis of goal-directed choice (Daw, Niv, & Dayan, 2005; Doya, Samejima, Katagiri, & Kawato, 2002). Although computationally expensive (Keramati, Dezfouli, & Piray, 2011; Otto, Raio, Chiang, Phelps, & Daw, 2013; Otto, Skatova, Madlon-Kay, & Daw, 2014), the "on-the-fly" binding of outcome probabilities with utilities offers adaptive advantage over more automatic action selection, which uses cached values based on reinforcement history (Sutton & Barto, 1998). There are, however, situations in which the processing cost of goal-directed computations does not yield the return of flexible control.

As an illustration, consider the scenario in Fig. 2.1A, which shows two available actions, A1 and A2, with bars representing the transition probabilities of each action into three potential outcome states, O1, O2, and O3. Here, the goal-directed approach prescribes that the agent retrieves each transition probability, estimates the current utility of each outcome, computes the product of each utility and associated probability, sums

Goal-Directed Decision Making
ISBN 978-0-12-812098-9, https://doi.org/10.1016/B978-0-12-812098-9.00002-4

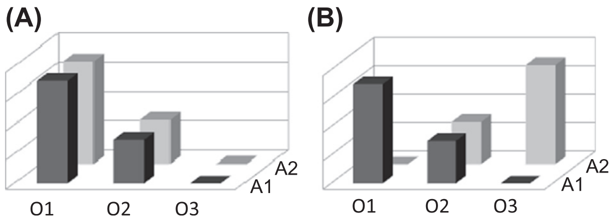

Figure 2.1 Probability distributions over three potential outcomes (O1, O2, and O3) for two available actions (A1 and A2) across which instrumental divergence is zero (1A) or high (1B).

across the resulting value distribution for each action, and, finally, compares the two action values. Of course, given equivalent costs, actions that have identical outcome distributions, as in Fig. 2.1A, will inevitably have the same value, eliminating the need for costly goal-directed computations. However, critically, this lack of instrumental divergence also eliminates the power of choice: Selecting A1 over A2, or vice versa, does not alter the probability of any given outcome state.

Now consider the scenario in Fig. 2.1B, in which the probability distribution of A2 has been reversed across the three outcomes, yielding high instrumental divergence. Note that if the utilities of O1 and O3 are the same, then according to conventional accounts of economic choice, from reinforcement learning (RL) theory to rational choice theory and prospect theory, all actions depicted in Fig. 2.1 have the same *expected utility*. Consequently, there should be no preference for the scenario depicted in Fig. 2.1B over that in Fig. 2.1A. And yet, if one considers the dynamic nature of subjective outcome utilities, the two scenarios clearly differ. To appreciate the significance of this difference, imagine that O1 and O3 represent food and water, respectively, and that at the point of choosing between the two scenarios, you are as hungry as you are thirsty. However, having committed, for example, to Fig. 2.1B, you might find that after a large meal without a drop to drink, your desire for O3 is suddenly greater than that for O1. A few hours later, having thoroughly quenched your thirst, you may again prefer O1. Unlike the scenario illustrated in Fig. 2.1A, the instrumental contingencies in Fig. 2.1B allow you to produce the currently desired outcome as preferences change, by switching between actions. Thus, even when expected utilities are presently the same, the possibility that outcome utilities may subsequently change renders the flexible control afforded by high instrumental divergence essential for long-term reward maximization. As such, high instrumental divergence may have intrinsic utility, eliciting a significant preference for the environment in Fig. 2.1B over that in Fig. 2.1A.

Theories of instrumental behavior distinguish between the goal-directed decisions described above, which are motivated by the probability and current utility of their consequences, and habitual actions, which are rigidly and automatically elicited by the stimulus environment based on their reinforcement history (Balleine & Dickinson, 1998). Although considerable evidence has substantiated this theoretical distinction, and in spite of its far-reaching implications, ranging from the structuring of economic policies to the treatment of compulsive pathology, very little is still known about what factors induce the use of one instrumental strategy over the other. As noted, when instrumental divergence is zero, the greater processing cost of goal-directed computations does not yield the return of flexible control, suggesting that a less resource-intensive, habitual, action selection strategy might be optimal. One possibility, therefore, is that a lack of instrumental divergence (i.e., a failure to map alternative actions to distinct outcome states) results in a degradation of goal-directed performance, eliciting a greater reliance on habitual control.

In this chapter, I will review behavioral and neural support for the role of instrumental divergence in goal-directed decision-making. I will begin by formalizing instrumental divergence as the information-theoretic distance between outcome distributions associated with available action alternatives, relating this novel decision variable to, and dissociating it from, a range of motivational and cognitive factors. I will then review recent work addressing the intrinsic utility of instrumental divergence, including its relevance to psychopathology, and, finally, discuss the potential role of instrumental divergence in the arbitration between goal-directed and habitual decision strategies.

AN INFORMATION-THEORETIC FORMALIZATION OF INSTRUMENTAL DIVERGENCE

Conceptually, instrumental divergence is simply the difference between outcome distributions associated with alternative actions. This concept can be formalized as the Jensen–Shannon (JS) divergence of instrumental outcome probability distributions. Let P_1 and P_2 be the respective outcome probability distributions for two available actions, O be the set of possible outcomes, and $P(o)$ be the probability of a particular outcome, o. The instrumental (JS) divergence is

$$ID = \frac{1}{2}\sum_{o \in O}\log\left(\frac{P_1(o)}{P_*(o)}\right)P_1(o) + \frac{1}{2}\sum_{o \in O}\log\left(\frac{P_2(o)}{P_*(o)}\right)P_2(o), \tag{2.1}$$

where

$$P_* = \frac{1}{2}(P_1 + P_2).$$

Note that instrumental divergence is defined here with respect to the sensory rather than motivational features of outcome states. Since subjective outcome utilities may change from one moment to the next (e.g., due to sensory satiety), a measure of divergence based on outcome utilities would be inherently unstable. Thus, a definition in terms of nonvalenced sensory features is critical for the broad, organizing, role of instrumental divergence posited here, which includes guiding the organism toward high-agency environments and signaling the need to switch to a habitual decision strategy. Note also that instrumental divergence is defined on distributions associated with *available* action alternatives: If P_1 and P_2 were outcome distributions associated with different cues, or with any other events not subject to the agents volition, their divergence, although relevant to the predictability of the outcome, would not be instrumental and, consequently, would have no implications for flexible instrumental control.

While JS divergence is only one of many distance measures, it has several advantages, including its symmetry and generality: It applies to nominal and numerical, discrete and continuous random variables, and it intuitively generalizes to any arbitrary finite number of probability distributions (Lin, 1991), allowing for comparisons of multiple action alternatives. JS divergence is also intimately related to Shannon entropy, a decision variable frequently shown to influence economic choice (Abler, Herrnberger, Grön, & Spitzer, 2009; Erev & Barron, 2005; Holt & Laury, 2005), that is greatest when the distribution over outcomes is uniform. Given a set of available actions, A, where $p(o|a)$ and $p(o,a)$ are, respectively, the conditional and joint probabilities of outcome o, the Shannon entropy is

$$H = -\sum_{a \in A} \sum_{o \in O} p(o, a) \log p(o|a). \tag{2.2}$$

In spite of the close relationship between the two measures (JS divergence is simply the symmetrized relative entropy), they have dramatically different implications: While Shannon entropy reflects uncertainty about the state of the outcome variable given performance of a particular action, or given a set of available actions as in Eq. (2.2), JS divergence, as applied here, reflects the degree to which discrimination and selection between available actions increases the controllability of the outcome. As discussed in the next section, these closely related information-theoretic variables elicit neural activity in distinct brain regions.

NEURAL CORRELATES OF INSTRUMENTAL DIVERGENCE

A large literature has identified neural signals scaling with trial-by-trial estimates of goal-directed action values (i.e., the expected utility of available response options) (Gläscher, Hampton, & O'doherty, 2008; Rangel & Hare, 2010; Wunderlich, Dayan, & Dolan, 2012; Wunderlich, Rangel, & O'Doherty, 2009). While instrumental divergence is not a measure of the value of performing a particular action (since it is defined with respect to sensory rather than motivational outcome features), it may improve the efficacy of such estimates by identifying instances in which a goal-directed decision strategy yields flexible control over outcomes. This marker of flexible control can then be used to guide the organism toward high-agency environments, to signal that a transition to habitual performance might be advantageous, or to restrict searches of the state—action space. Given these important characteristics, one might expect a neural signature of instrumental divergence to be present during human goal-directed performance, dissociable from the well-established neural correlates of action values. In this section, I will review prominent formal accounts of goal-directed action values, highlighting their relevance to, and recently demonstrated neural dissociation from, instrumental divergence.

Formal accounts of goal-directed action values: Early accounts of goal-directed performance formalized the strength of the action—reward relationship as the difference between two conditional probabilities; the probability of gaining a target reward (*r*), given that a specific action (*a*) is performed and the probability of gaining the reward in the absence of that action ($\sim a$) (Hammond, 1980):

$$\Delta P = p(r|a) - p(r|\sim a). \tag{2.3}$$

Sensitivity to this "instrumental contingency" is a defining property of goal-directed actions that has been reliably demonstrated in humans (Chatlosh, Neunaber, & Wasserman, 1985; Liljeholm, Tricomi, O'Doherty, & Balleine, 2011; Shanks & Dickinson, 1991) as well as rodents (Balleine & Dickinson, 1998; Hammond, 1980). Instrumental divergence can be characterized as a generalization of the instrumental contingency rule, extending the contrast over multiple actions and sensory-specific outcomes. The representational change achieved by this simple extension is profound; while the instrumental contingency is a signed measure of the relative advantage of performing a particular action, instrumental divergence is a symmetric measure of the degree to which discrimination and selection between actions alters the probabilities of potential outcome states (i.e., the degree of flexible instrumental control).

A more recent formal framework that represents the full sensory-specific outcome distributions of alternative actions is model-based RL (e.g., Daw et al., 2005). Specifically, for each action available in the current state, and for all possible outcome states, model-based RL maintains separate representations of the probability of transitioning into a possible subsequent state, given that a particular action is performed in the current state, $T(s,a,s')$, and the reward associated with that subsequent state, $R(s')$. Transition probabilities and rewards are dynamically combined, at each choice point, to yield action values:

$$Q(s,a) = \sum_{s'} T(s,a,s')^* \left[r(s') + \gamma \max_{a'} Q(s',a') \right], \tag{2.4}$$

where $Q(s',a')$ is the, recursively defined, value of an action performed in the subsequent state and γ is a discount parameter. The transition probabilities may be presumed to be known, or may be incrementally acquired based on trial-by-trial feedback, using a state prediction error:

$$T(s,a,s') = T(s,a,s') + \eta(1 - T(s,a,s')), \tag{2.5}$$

where η is the learning rate. Note that, although sensory-specific transition probabilities are explicitly estimated and represented, they are used solely in the service of generating action values, through their combination with outcome utilities. In contrast, the argument set forth in this chapter is that sensory-specific transition probabilities are also used to estimate instrumental divergence, which is in turn used to guide the deployment of goal-directed processes.

Neural correlates of motivational and information-theoretic variables: As a first step in evaluating the representation of instrumental divergence in goal-directed processes, Liljeholm, Wang, Zhang, and O'Doherty (2013) used fMRI to investigate a neural signal scaling with instrumental divergence, and the dissociability of such a signal from the effects of other motivational and information-theoretic variables. On each trial in their choice task, participants selected between two available actions, given a set of food treats potentially produced by those actions (see Fig. 2.2A). The probability distributions over food treats, including a "no treat" outcome, for four distinct action alternatives were trained to criterion prior to the choice task, and this procedure was repeated in each of three consecutive blocks, using different probabilities and food treats in each block, to ensure sufficient variance. The subject-specific utilities of food treats were assessed using evaluative pleasantness ratings and a standard, incentive compatible, Becker–DeGroot–Marschak auction (Becker, DeGroot, & Marschak, 1964).

Liljeholm et al. (2013) modeled the BOLD response during the choice period of each trial as a function of the instrumental divergence between the actions available on the trial and the values of those actions derived using model-based RL. Consistent with previous work (Gläscher et al., 2008; Wunderlich et al., 2012, 2009), they found that the value of the chosen action scaled with activity in the ventromedial prefrontal cortex: In contrast, instrumental divergence correlated with activity in the right supramarginal gyrus of the inferior parietal lobule (IPL)—a region previously implicated in the planning, execution, and observation of goal-directed actions (Fincham, Carter, Van Veen, Stenger, & Anderson, 2002; Liljeholm, Molloy, & O'Doherty, 2012; Liljeholm et al., 2011). Importantly, the effect of instrumental divergence in the IPL was also dissociable from other information-theoretic and motivational variables, such as the entropy of outcome distributions for chosen actions, which scaled with activity in the dorsolateral prefrontal cortex (DLPFC), and the summed utility of potential food treats, which elicited activity in the insula and ventral striatum (see Fig. 2.2B). A Bayesian model selection analysis ruled out additional competing variables, such as the difference between reward probabilities associated with available action alternatives (i.e., the absolute value of ΔP) and the overall probability of reward on each trial, as sources of the IPL activity. It should be noted that a BOLD signal scaling with instrumental divergence says very little about how a distributed neural code of instrumental divergence may be implemented—an important question for future work. Nonetheless, the identification of a neural signal scaling with instrumental divergence during instrumental choice performance supports

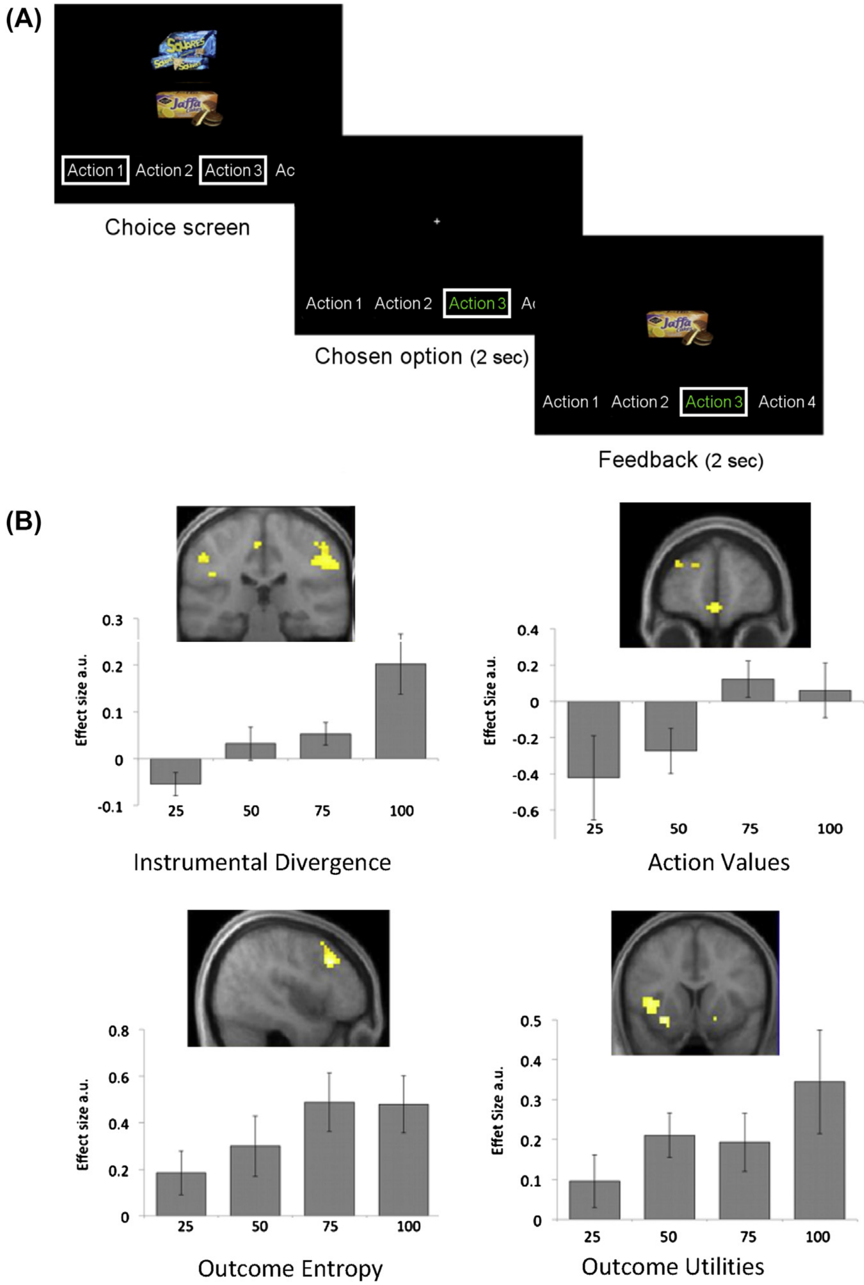

Figure 2.2 (A) Illustration of a trial in the choice task, with the choice screen showing two available actions and the food treats potentially produced by those actions. (B) Parametric modulation, during the choice screen period of each trial, of activity in the IPL by instrumental divergence (top left), of ventromedial prefrontal cortex activity by the value of the chosen action (top right), of DLPFC activity by the outcome entropy for the chosen action (bottom left), and of anterior insula and ventral striatum by the summed utility of potential outcomes (bottom right). *(Task and results from Liljeholm et al. (2013).)*

the notion that this variable may play an important role in decision-making. In subsequent sections, I discuss more direct, behavioral evidence for an influence of instrumental divergence on goal-directed choice.

INSTRUMENTAL DIVERGENCE AND THE INTRINSIC UTILITY OF CONTROL

Imagine that you had to commit, for some duration, to one of the two environments illustrated in Fig. 2.1A and B, and that, at the time of making your decision, the subjective utilities of O1 and O3 were identical, yielding identical expected values for all actions across environments. If outcome utilities were static, the high instrumental divergence afforded by the probability distributions in Fig. 2.1B would be of little consequence. In the real world, however, subjective outcome utilities are constantly changing, due, for example, to sensory-specific satiety or changes in motivational states. Given this dynamic nature of subjective utilities, the high instrumental divergence in Fig. 2.1B is essential for long-term reward maximization and, as such, may have intrinsic utility, serving to motivate and reinforce decisions that guide the agent toward environments that enable flexible instrumental control. In this section, I review recent research investigating the intrinsic utility of instrumental divergence, its dissociability from related constructs, such as outcome diversity and free choice, and its role in psychopathology.

An experimental test of the utility of flexible instrumental control: A recent study by Mistry and Liljeholm (2016) investigated the intrinsic utility of flexible instrumental control using a novel paradigm, illustrated in Fig. 2.3, in which participants choose between environments with either high or low instrumental divergence. Specifically, participants assumed the role of a gambler in a casino, playing a set of four slot machines (i.e., alternative actions, respectively labeled A1—A4) that yielded three differently colored tokens, each worth a particular amount of money, with different probabilities. In each of several gambling rounds, participants were required to first select a "room" in which only two slot machines were available, and they were restricted to playing on those two machines on subsequent trials within that round. Critically, the two slot machines available in a room had either identical probability distributions over token outcomes, yielding zero divergence (as in Fig. 2.1A), or symmetrically opposite distributions, yielding relatively high divergence (as in Fig. 2.1B). The measure of interest, thus, was the decision at the beginning of each block (top of Fig. 2.3), between a high- versus zero-divergence room.

While the probabilities with which each slot machine yielded each colored token were fixed throughout the task, and pretrained to criterion prior to gambling, the monetary values assigned to different token colors changed intermittently and unpredictably (about every fourth gambling round on average). In addition to mimicking

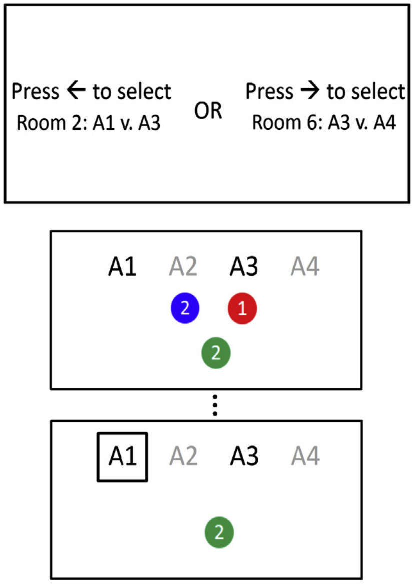

Figure 2.3 Illustration of task used by Mistry and Liljeholm (2016), showing the choice screen at the onset of a round (top) and the choice (middle) and feedback (bottom) screens on a trial within the round.

changes in the utilities of natural rewards, these changes in monetary values served to vary expected monetary utilities across gambling rooms, confirming that participants were sensitive to monetary payoffs, and to pit conventional currency against the utility of flexible control. Thus, while in some rounds, room options differed only in terms of instrumental divergence, in other rounds, expected monetary payoffs also differed across rooms, in either the same or opposite direction of instrumental divergence.

When participants choose between two gambling rooms with identical expected monetary payoffs but different levels of instrumental divergence, they choose the high-divergence room about 70% of the time, confirming a strong preference for flexible instrumental control all else being equal. Of primary interest, however, is how participants responded when high instrumental divergence was pitted against monetary gain. Here, alternative formal predictions may be generated using model-based RL agents that either do or do not consider the utility of flexible control. Specifically, the term $r(s')$ in Eq. (2.4) can be defined solely in terms of monetary reward, $r(s') = m(s')$, or in terms of both monetary reward and instrumental divergence, $r(s') = m(s') + w{*}ID(s')$, where w is a free parameter accounting for individual differences in the perceived utility of flexible control. Using a softmax distribution to translate action values into action probabilities, and fitting free parameters to choice data by minimizing negative log likelihood, we can derive a prediction, by each model, regarding the proportion of choosing the room with a greater expected monetary payoff when

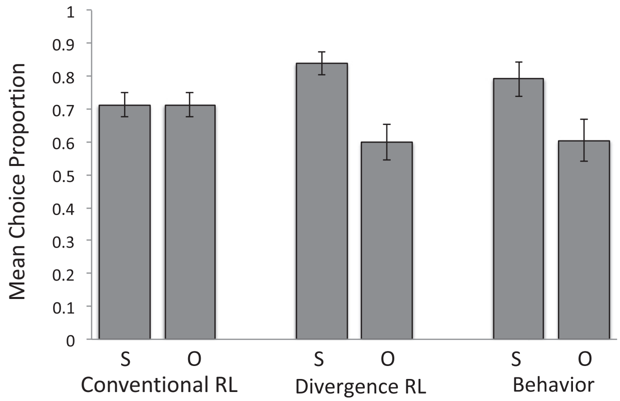

Figure 2.4 RL predictions and mean choice proportions from Experiment 1 by Mistry and Liljeholm (2016). Mean proportion of selecting the room with a greater expected monetary payoff when instrumental divergence differed across rooms in either the same (S) or opposite (O) directions, for a conventional RL model, an RL model that considers the utility of instrumental divergence, and behavioral choices. Error bars = SEM. *RL*, reinforcement learning.

instrumental divergence differs across rooms in either the same or opposite direction. Fig. 2.4 shows these predictions, for each model, together with the actual proportion of choices made by participants.

The conventional RL agent is, of course, likely to select the room with a greater monetary payoff whether the instrumental divergence of that room is zero or relatively high. In contrast, the divergence RL agent is significantly more likely to select the room with greater expected monetary payoff when that room also has relatively high instrumental divergence than when it has zero divergence. This was also the case with participants' choice behavior: The preference for a room with greater expected monetary payoff was significantly reduced when that room had zero instrumental divergence, and the alternative room, associated with a lower expected monetary payoff, had relatively high instrumental divergence. As a result, the divergence RL agent provides a significantly better fit to behavior than does the conventional model. Note that, when instrumental divergence differed across rooms in the opposite direction of monetary reward, the utility of flexible control was directly pitted against that of monetary gain. The reduction in preference, thus, shows a willingness to incur a monetary loss for access to high instrumental divergence. A parametric search for the exact trade-off between instrumental divergence and monetary reward, and investigation of the common neural value-scale mediating such trade-offs, is an important avenue for future work.

Instrumental divergence, perceptual outcome diversity, and free choice: The idea of "portfolio diversification"—mixing a wide variety of investments in order to reduce the impact of a single poorly performing source—is fundamental to theories of risk management. Ayal and Zakay (2009) conducted a series of psychological experiments in which participants choose among various "betting pools," where the perceptual diversity of betting options varied while the expected monetary gain was held constant. They found a significant preference for the most perceptually diverse pool and further, that the effort to maximize perceptual diversity sometimes led participants to prefer alternatives with lower expected monetary gain (see Schwartenbeck et al., 2015 for similar results). In the study by Mistry and Liljeholm described earlier, the perceptual diversity of obtainable outcomes was greater in high-divergence rooms than in zero-divergence rooms. Specifically, in zero-divergence rooms, there was a high probability of obtaining a blue token, a relatively low probability of obtaining a red token, and a zero probability of obtaining a green token (with specific token colors counterbalanced across participants). In contrast, in high-divergence rooms, participants were able to obtain blue, red, *and* green tokens by switching between actions across trials. Consequently, even when the expected monetary gain of high- and zero-divergence rooms was identical, the perceptual diversity of obtainable outcomes was greater in high-divergence rooms than in zero-divergence rooms.

Now, consider a scenario in which a computer algorithm chooses between the actions in a particular gambling room, selecting each action equally often by alternating across trials. Given such absence of voluntary choice, the high-divergence room no longer yields flexible instrumental control. Indeed, in the absence of free choice, neither the high- nor zero-divergence condition can be considered instrumental. However, such a computer algorithm would still yield greater perceptual diversity in high-divergence rooms than in zero-divergence rooms. Consequently, if choices were driven by a desire to maximize perceptual diversity, rather than instrumental divergence, they should not differ depending on whether the participant or an alternating computer algorithm chooses between the actions in a room. In a second study, Mistry and Liljeholm used an "autoplay" option, in which the computer selected between the two actions available in a room, to rule out perceptual outcome diversity as the source of a preference for flexible instrumental control. Specifically, in each block, one room option was always self-play—participants choose freely between actions available in the selected room—and the other option was always autoplay—a computer algorithm alternated between actions across trials—as indicated by labels printed below options on the room-choice screen. Instrumental divergence was either the same (high or zero) or different across room options.

The results of the study are shown in Fig. 2.5. When choosing between a high-divergence and a zero-divergence room (left two bars), participants preferred the high-divergence room when it was self-play (while the zero-divergence room was autoplay) but had no preference when the high-divergence room was autoplay (and the zero-divergence room was self-play). Since the high-divergence room was always associated with greater perceptual diversity, these results suggest that preferences were instead driven, as hypothesized, by instrumental divergence. The self-play versus autoplay

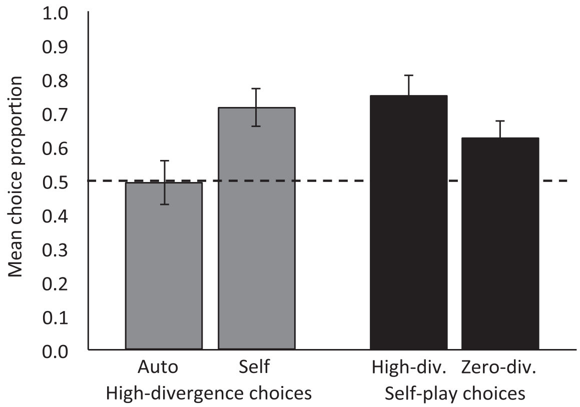

Figure 2.5 Mean choice proportions from Experiment 2 reported by Mistry and Liljeholm (2016). Mean proportions of high-divergence choices over zero-divergence choices (left) for blocks in which the high-divergence option was autoplay (Auto) versus blocks in which the high-divergence option was self-play (Self), and mean proportions of self-play choices over autoplay choices (right) for blocks in which both options had high divergence (High-div.) versus blocks in which both options had zero divergence (Zero-div.). *Dashed lines* indicate chance performance. Error bars = SEM.

manipulation is also related to a well-established preference for free choice over forced choice demonstrated across species, from pigeons to primates, including humans (Catania & Sagvolden, 1980; Leotti & Delgado, 2011, 2014; Suzuki, 1999). In Mistry and Liljeholm's second study, when instrumental divergence was held constant across self-play and autoplay options, participants choose the self-play over autoplay room significantly more often when both rooms had high instrumental divergence than when both rooms had zero instrumental divergence (right two bars in Fig. 2.5), suggesting that the value of choice depends less on whether a decision is voluntarily made and more on the extent to which decisions have a meaningful impact on future states.

Instrumental divergence and psychopathology: An aberrant experience of instrumental control, or "sense of agency" (SOA), is a common characteristic of various psychiatric disorders (Haggard, Martin, Taylor-Clarke, Jeannerod, & Franck, 2003; Keeton, Perry-Jenkins, & Sayer, 2008; Maeda et al., 2012; Martin & Penn, 2002; Peterson & Seligman, 1984; Seligman, Abramson, Semmel, & Von Baeyer, 1979; Voss et al., 2010; Werner, Trapp, Wüstenberg, & Voss, 2014): Schizophrenic individuals, in particular, differ from healthy controls in their self versus external attributions of events, as well as in the degree of intentional binding—a perceived compression of the time interval between an action and its consequence (Haggard et al., 2003; Maeda et al., 2012; Martin & Penn, 2002; Voss et al., 2010; Werner et al., 2014). While operational definitions of agency and volition differ across such findings, they share some fundamental limitations: First, they often conflate the estimation or representation of an action–outcome contingency with the subjective experience of volitional control (e.g., by manipulating outcome entropy or contiguity). Second, they tend to focus exclusively on cognitive or perceptual judgments, thus failing to address motivational aspects of SOA. In contrast, instrumental divergence provides a novel measure of agency that varies independently of outcome contiguity and predictability, and without eliminating volition, thus disambiguating the contribution of basic instrumental processes, such as simple contingency learning, to the apparent dysregulation of agency in schizophrenia. Moreover, unlike previous assessments of SOA, our task assessing a preference for high instrumental divergence can dissociate motivational aspects of flexible instrumental control from purely cognitive representations, at both behavioral and neural levels.

In a recent, unpublished, study, to begin to address the nature of aberrant SOA in schizophrenia, particularly with respect to its role in motivated behavior, we used the Oxford–Liverpool Inventory of Feelings and Experiences (O-LIFE) (Mason, Claridge, & Jackson, 1995) to relate individual differences in schizotypy to performance on the task used in the second study by Mistry and Liljeholm, discussed in the previous section. The O-LIFE questionnaire measures four dimensions of schizotypy—unusual experiences, cognitive disorganization, introvertive anhedonia, and impulsive nonconformity. We found that scores on the dimensions of unusual experiences and introvertive anhedonia, phenomenologically related, respectively, to positive and negative symptoms of schizophrenia, predicted a preference for high instrumental divergence. Specifically, as illustrated in Fig. 2.6, scores on both of these dimensions were significantly, negatively, correlated with the proportion of high-divergence choices over zero-divergence choices when the high-divergence option was self-play and with the proportion of self-play over autoplay choices when both options had high divergence. In contrast, there was no significant correlation between any schizotypy dimension and the proportion of choices for options that did not involve high instrumental divergence - i.e., rooms with high divergence but auto-play, or with zero divergence and self-play; indeed, neither of these latter choice proportions deviated significantly from chance, suggesting a complete lack of preference for either perceptual diversity or self-play in the absence of instrumental divergence. Moreover, no schizotypy dimension predicted preferences for greater monetary pay-offs, specifically implicating the utility of agency as a target for modulation in schiotypy.

The finding that schizotypal traits in healthy individuals modulate a preference for high instrumental divergence suggests that effects of instrumental divergence might also be significantly altered in clinical populations, potentially accounting for aspects of behavioral pathology in schizophrenia. Notably, the supramarginal gyrus of the IPL, implicated in neural computations of instrumental divergence by Liljeholm et al. (2013), has been frequently shown to differ volumetrically across schizophrenic and neurotypical individuals (Buchanan et al., 2004; Goldstein et al., 1999; Peng et al., 1994; Pol et al., 2001; Zhou et al., 2007), highlighting a possible anatomical basis

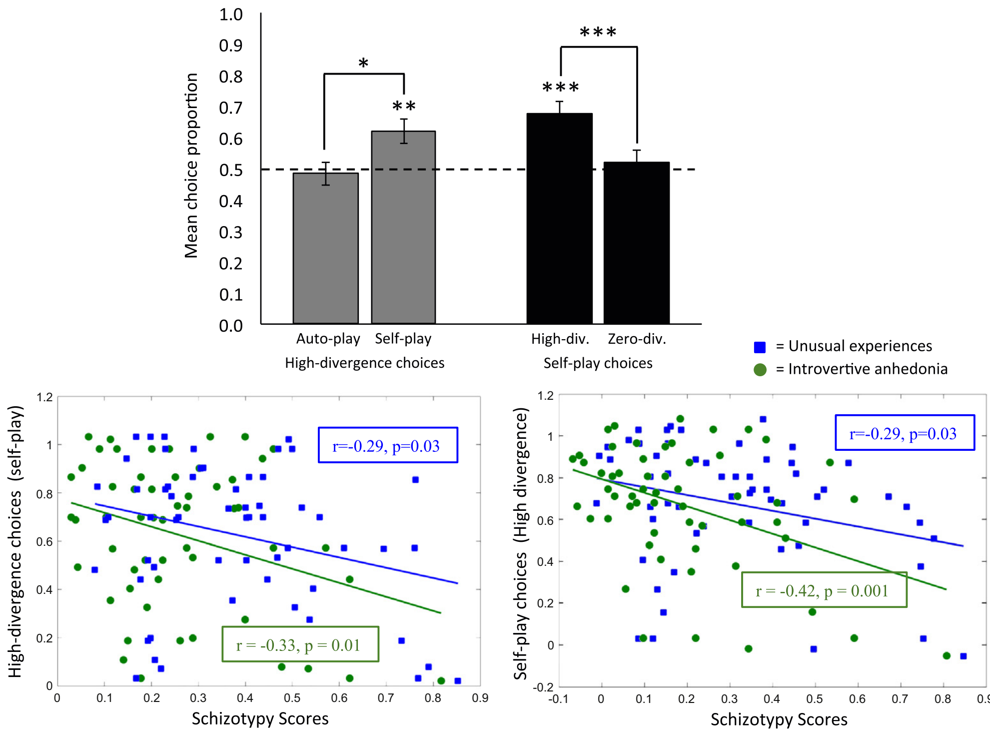

Figure 2.6 Results from a preliminary study (n = 60) assessing the relationship between schizotypal traits and a preference for high instrumental divergence. Top: Mean choice proportions for the same conditions as those listed in Fig. 2.5. Error bars = SEM. *Dashed line* indicates chance performance. * = $P < .05$, ** = $P < .005$, *** = $P < .0001$. Bottom: Residual plots of choice proportions and schizotypy scores (points scored out of total possible), adjusted for the number of training blocks to criterion on action–outcome probabilities, and for the order of Oxford–Liverpool Inventory of Feelings and Experience administration (i.e., before or after the gambling task).

for any differences in cognitive or motivational representations of instrumental divergence. Future research will be aimed at assessing whether individuals diagnosed with schizophrenia differ from healthy controls in their behavioral preference for high instrumental divergence and in underlying neural value computations.

INSTRUMENTAL DIVERGENCE AS A BOUNDARY CONDITION ON GOAL-DIRECTEDNESS

Unlike goal-directed decisions, habitual performance is insensitive to the current utility of action outcomes: an inflexibility that has been argued to result from a model-free RL process, in which instrumental responses come to be rigidly elicited by the stimulus environment based on their reinforcement history (Daw et al., 2005). Specifically, for a given action performed in a particular state, the model-free action value is updated as

$$Q(s, a) \leftarrow Q(s, a) + \alpha[(r(s') + \gamma Q(s', a')) - Q(s, a)], \tag{2.6}$$

where α is the learning rate and remaining terms are defined as for Eq. (2.4). Critically, the value of an action is updated *following* its execution in a particular state, only to be stored and not retrieved until the agent reenters that state. Consequently, model-free action selection reflects only past reinforcement, without regard for the current utility of future states. The flexibility of goal-directed decisions, while computationally expensive (Keramati et al., 2011; Otto et al., 2013, 2014), offers a clear adaptive advantage over such cached retrieval. However, as noted, when instrumental divergence is very low, the greater processing cost of goal-directed computations does not yield the return of flexible instrumental control, suggesting that a less resource-intensive, habitual, strategy might be optimal. One possibility, therefore, is that instrumental divergence serves as a boundary condition on the deployment of goal-directed behavior, increasing reliance on "fast and frugal" habits in environments that inherently impede flexibility.

In this section, I review evidence from the rodent literature suggesting that reliance on a goal-directed versus habitual strategy might depend on the degree of instrumental divergence. I then discuss a recent human neuroimaging study assessing the role of instrumental divergence in biasing behavior toward goal-directed versus habitual control, and sketch a formal description of such arbitration.

Instrumental divergence and behavior–reward correlations: In a series of seminal paper, Dickinson et al. demonstrated that goal-directed sensitivity to current outcome values depends on both the extent and nature of instrumental training: First, extensive but not moderate training produced insensitivity to outcome devaluation (Adams, 1982). Second, and more intriguingly, even moderate training resulted in devaluation insensitive performance if animals were trained on an interval schedule, in which reward delivery depends on the time elapsed since the last reward, but not if they were trained on a ratio schedule, in which the delivery of reward depends on the number of responses since the last reward (Dickinson, Nicholas, & Adams, 1983). Another clue to what factors may influence goal-directed and habitual arbitration came with a couple of demonstrations by Colwill and Rescorla (1990), showing that, contrary to the reports by Dickinson et al., animals remained sensitive to outcome devaluation in spite of being extensively trained on an interval schedule. A critical difference in methods was that, while Dickinson et al. used a single lever yielding a single outcome, Colwill and Rescorla trained animals on two different instrumental responses, each yielding a distinct sensory-specific reward. Holland (2004) directly contrasted these two procedures, demonstrating that, indeed, performance remains sensitive to outcome devaluation in spite of extensive training on an interval schedule when different instrumental responses yield distinct sensory-specific outcomes but not when alternative responses yield the same outcome.

Dickinson (1985) suggested that the critical factor arbitrating between goal-directed and habitual performance might be the correlation between variations in response performance and variations in obtained outcomes. Dickinson noted that animals tended to show relatively large variations in performance across early training sessions but exhibited a consistently high rate of responding with extended training. He concluded that, rather than the extent of training per se, it was the reduced variation in performance during late training stages, and the resulting reduction in the behavior—reward correlation, that was responsible for devaluation insensitive performance. This framework also predicts the differences between ratio and interval schedules: On an interval schedule, no amount of responding will yield reward until a particular interval has passed; once the interval has passed, a single reward is delivered given a response, whether that response was preceded by 1, 10, or 100 responses. In other words, variations in response rates have virtually no impact on the reward rate. In contrast, on a ratio schedule, the number of obtained rewards increases linearly with the number of responses. As with response—reward correlations, instrumental divergence, defined over the quantitative variables of response and reward rate, increases across interval and ratio schedules. Moreover, instrumental divergence is greater whenever qualitatively different instrumental responses yield distinct sensory-specific outcomes, as in the studies by Colwill and Rescorla (1990) and Holland (2004). Thus, the notion that instrumental divergence arbitrates between goal-directed and habitual performance is an extension of Dickinson's "behavior—reward correlation" theory to the case of multiple actions and sensory-specific outcomes.

A study assessing the role of instrumental divergence in strategy arbitration: In a recent neuroimaging study, Liljeholm, Dunne, & O'doherty (2015) employed a task aimed at encouraging goal-directed versus habitual responding using environments with high versus zero instrumental divergence. Specifically, in this task (illustrated in Fig. 2.7A), participants had to maintain the balance of a virtual system of fluid-filled beakers, using four distinct actions across four abstract cues, in order to avoid incurring a rapidly cumulating monetary loss. As long as all beakers had sufficient fluid, system balance was maintained and yielded continuous monetary reward. However, on each trial, one of the beakers would be emptied causing "system imbalance" and monetary loss until the participant refilled the beaker by performing a particular instrumental action. The emptying of a beaker was accompanied by the onset of one of four abstract cues. In a high-divergence condition, each action deterministically and uniquely regulated a particular beaker, so that there was no overlap between the sensory-specific outcome probability distributions of the four actions. Conversely, in the zero-divergence condition, each abstract cue signaled that a particular action would be effective in regulating any beaker that needed to have its fluid refilled at the moment, regardless of the identity of that beaker: Consequently, across trials, while each action was paired with a specific antecedent cue, it was decorrelated from the refilling of any particular beaker, generating a complete overlap of sensory-specific outcome probability distributions associated with alternative actions.

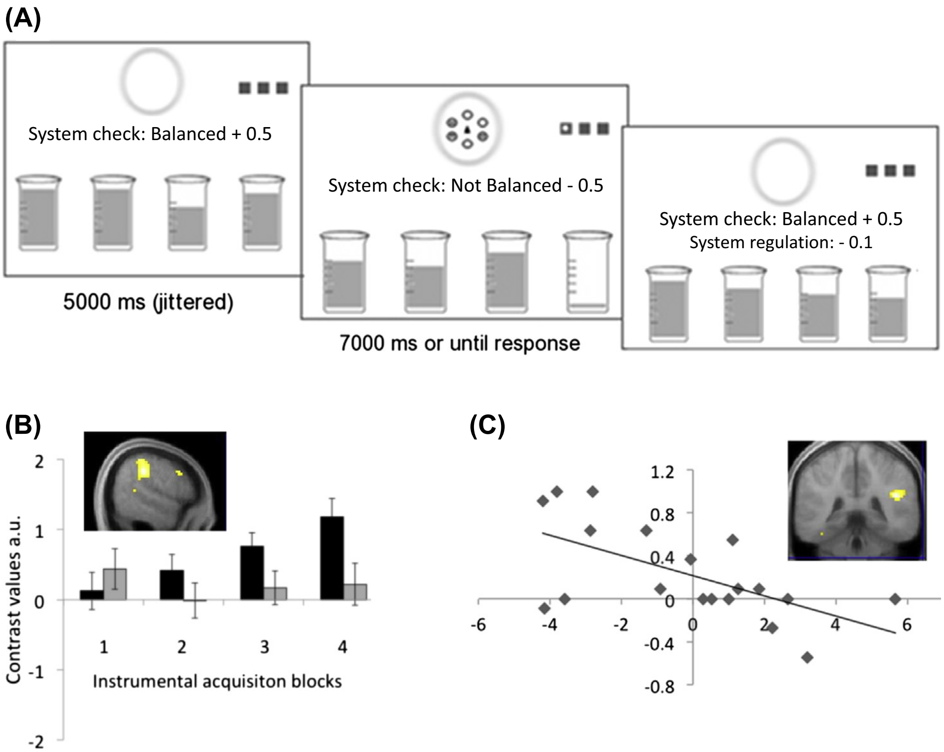

Figure 2.7 (A) Illustration of a trial in the beaker regulation task. (B) Increases in IPL activity across acquisition blocks in the high-divergence condition but not the zero-divergence condition. (C) Correlation between differences in IPL activity (x-axis) and differences in devaluation insensitivity (y-axis) across high- and zero-divergence conditions. *IPL*, inferior parietal lobule. *(Task and results from Liljeholm et al. (2015).)*

Following acquisition of the system-balancing task, one of the beakers was "devalued": Specifically, participants were instructed, as well as given the opportunity to passively observe across several trials, that one of the beakers was no longer relevant for system balance, which would be maintained, and continue to yield points, even when the liquid in this beaker dropped below threshold. Having correctly identified the devalued beaker, participants were allowed to again regulate the beaker system in a final test phase. Defining any response aimed at refilling the now devalued beaker as habitual (i.e., as devaluation insensitive), Liljeholm et al. found significantly greater habitual test performance in the zero-divergence than in the high-divergence condition. At the neural level, during the initial acquisition phase, activity in the supramarginal gyrus of the IPL, the region found by Liljeholm et al. (2013) to encode instrumental divergence, increased across blocks of acquisition in the high-divergence, but not the zero-divergence, condition (see Fig. 2.7B). Moreover, in the test phase, differences in IPL activity across high- and zero-divergence conditions predicted behavioral differences in habitual performance (Fig. 2.7C). It should be noted that the task employed by Liljeholm et al. (2015) was quite complex, with several factors (e.g., the strong stimulus control in the zero-divergence condition or the threat of cumulative loss) potentially contributing to neural and behavioral effects. Nonetheless, the results provide compelling initial evidence for a role of instrumental divergence in the arbitration between decision strategies, while also corroborating previous work implicating the IPL in a neural representation of instrumental divergence.

Formalizing arbitration by instrumental divergence: While a fully specified computational account of arbitration between goal-directed and habitual control by instrumental divergence is beyond the scope of this chapter, a preliminary sketch might characterize the probability of deploying a goal-directed versus habitual strategy as a logistic function of instrumental divergence, ID, such that

$$
\begin{aligned}
P(Q_{MB}(s,a)) &= \frac{1}{1+\exp^{-A(ID-B)}} \\
&\text{and} \\
P(Q_{MF}(s,a)) &= 1 - P(Q_{MB}(s,a))
\end{aligned}
\tag{2.7}
$$

where $P(Q_{MB}(s,a))$ and $P(Q_{MF}(s,a))$ are probabilities of using model-based and model-free action values respectively, B is a free parameter indicating the value of instrumental divergence at which the two control strategies are equally likely, and A specifies the strength of the bias toward a particular control strategy as instrumental divergence deviates from the indifference point set by B. Reasonable constraints on B would be the lower, 0, and upper, $\log(n)$, bounds of instrumental divergence, where n is the number of actions (i.e., outcome distributions) being considered. This simple rule predicts an increased reliance on goal-directed, over habitual, behavioral control with increasing levels of instrumental divergence.

OPEN QUESTIONS AND CONCLUDING REMARKS

In this chapter, I have reviewed some empirical evidence for the role of instrumental divergence—a formal index of flexible instrumental control—in goal-directed choice. In particular, I have addressed the utility of instrumental divergence, operationally defined as a preference for high-divergence environments, and the use of instrumental divergence as a boundary condition on the deployment of goal-directedness. At the neural level, I have discussed two studies implicating the supramarginal gyrus of the IPL—a region previously linked to a range of goal-directed processes—in the representation of instrumental divergence. While this recent work offers compelling preliminary evidence for the importance of instrumental divergence as a psychological construct, several critical questions remain open, many of which have been noted throughout this chapter. In this section, I will focus on two issues fundamental to the representation and implementation of instrumental divergence.

First, at the core of the proposal set forth in this chapter is the notion that instrumental divergence has intrinsic utility, serving both to justify the processing cost of goal-directed computations and to motivate decisions that guide the organism toward high-agency environments. But where exactly does this utility come from? In Instrumental divergence and the intrinsic utility of control section, I modeled the utility of instrumental divergence by including it as a reward surrogate in a model-based RL algorithm. This approach makes two assumptions: First, instrumental divergence is an explicitly represented variable and second, the apparent utility is directly attached to this variable, either a priori or through experience. An alternative possibility is that the agent assumes that subjective utilities may change over time, computing the values of future states and actions over a set of possible configurations of subjective utilities. Returning to the example provided in the introduction, given a choice between the scenarios depicted in Fig. 2.1A and B, respectively, and given that the subjective utilities of O1 and O3 are the same at the time of choosing, if the agent considers an array of possible changes in those subjective utilities, computing model-based action values over all possibilities, then the high-divergence scenario depicted in Fig. 2.1B would likely yield the greatest expected utility, since it allows the agent to select, for each hypothesized future utility configuration, the action that yields the outcome with greatest hypothetical utility. Thus, it is possible that an influence of instrumental divergence on choice preferences, such as that demonstrated by Mistry and Liljeholm (2016), could emerge in the absence of any explicit representation of instrumental divergence.

The nature of its apparent utility notwithstanding, if instrumental divergence is an explicitly represented variable, as suggested by the neural correlates identified by Liljeholm et al. (2013), another fundamental question is how exactly this construct is implemented neurally. In other words, is there a distributed neural code that carries information about the extent to which alternative actions differ with respect to their outcome distributions, analogous to the computation specified in Eq. (2.1)? A possible solution to this problem might be a neural network that discriminates between actions based on their outcome distributions. Specifically, initial layers in the network might retrieve the sensory-specific outcome features associated with distinct action alternatives, and those outcome features would then serve as inputs to subsequent layers that identify individual actions: The greater the decoding of action identities by the output layer of this network, the greater the instrumental divergence of considered action alternatives.

In conclusion, in addition to a range of open questions regarding its specific effects on decision-making, more fundamental aspects of instrumental divergence, such as the computational basis of its apparent utility, and the architecture of its neural implementation, must also be addressed by a comprehensive account. Clearly, assessment of the role of instrumental divergence in goal-directed choice is still in its infancy. Nonetheless, the initial findings reviewed in this chapter—ranging from a behavioral influence on choice preferences and devaluation sensitivity to neural signaling in a region frequently implicated in goal-directed control—promise exciting possibilities.

ACKNOWLEDGMENTS

The writing of this chapter was funded by a CAREER grant from the National Science Foundation (1654187) awarded to Mimi Liljeholm. The author thanks Richard Morris for helpful discussion.

REFERENCES

Abler, B., Herrnberger, B., Grön, G., & Spitzer, M. (2009). From uncertainty to reward: BOLD characteristics differentiate signaling pathways. *BMC Neuroscience, 10*(1), 154.

Adams, C. D. (1982). Variations in the sensitivity of instrumental responding to reinforcer devaluation. *The Quarterly Journal of Experimental Psychology, 34*(2), 77–98.

Ayal, S., & Zakay, D. (2009). The perceived diversity heuristic: The case of pseudodiversity. *Journal of Personality and Social Psychology, 96*(3), 559.

Balleine, B. W., & Dickinson, A. (1998). Goal-directed instrumental action: Contingency and incentive learning and their cortical substrates. *Neuropharmacology, 37*(4), 407–419.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Systems Research and Behavioral Science, 9*(3), 226–232.

Buchanan, R. W., Francis, A., Arango, C., Miller, K., Lefkowitz, D. M., McMahon, R. P., … Pearlson, G. D. (2004). Morphometric assessment of the heteromodal association cortex in schizophrenia. *American Journal of Psychiatry, 161*(2), 322–331.

Catania, A. C., & Sagvolden, T. (1980). Preference for free choice over forced choice in pigeons. *Journal of the Experimental Analysis of Behavior, 34*(1), 77–86.

Chatlosh, D. L., Neunaber, D. J., & Wasserman, E. A. (1985). Response-outcome contingency: Behavioral and judgmental effects of appetitive and aversive outcomes with college students. *Learning and Motivation, 16*(1), 1–34.

Colwill, R. M., & Rescorla, R. A. (1990). Effect of reinforcer devaluation on discriminative control of instrumental behavior. *Journal of Experimental Psychology: Animal Behavior Processes, 16*(1), 40.

Daw, N. D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. *Nature Neuroscience, 8*(12), 1704–1711.

Dickinson, A. (1985). Actions and habits: The development of behavioural autonomy. *Philosophical Transactions of the Royal Society of London B: Biological Sciences, 308*(1135), 67–78.

Dickinson, A., Nicholas, D. J., & Adams, C. D. (1983). The effect of the instrumental training contingency on susceptibility to reinforcer devaluation. *The Quarterly Journal of Experimental Psychology, 35*(1), 35–51.

Doya, K., Samejima, K., Katagiri, K. I., & Kawato, M. (2002). Multiple model-based reinforcement learning. *Neural Computation, 14*(6), 1347–1369.

Erev, I., & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review, 112*(4), 912.

Fincham, J. M., Carter, C. S., Van Veen, V., Stenger, V. A., & Anderson, J. R. (2002). Neural mechanisms of planning: A computational analysis using event-related fMRI. *Proceedings of the National Academy of Sciences, 99*(5), 3346–3351.

Gläscher, J., Hampton, A. N., & O'doherty, J. P. (2008). Determining a role for ventromedial prefrontal cortex in encoding action-based value signals during reward-related decision making. *Cerebral Cortex2, 19*(2), 483–495.

Goldstein, J. M., Goodman, J. M., Seidman, L. J., Kennedy, D. N., Makris, N., Lee, H., … Tsuang, M. T. (1999). Cortical abnormalities in schizophrenia identified by structural magnetic resonance imaging. *Archives of General Psychiatry, 56*(6), 537—547.

Haggard, P., Martin, F., Taylor-Clarke, M., Jeannerod, M., & Franck, N. (2003). Awareness of action in schizophrenia. *Neuroreport, 14*(7), 1081—1085.

Hammond, L. J. (1980). The effect of contingency upon the appetitive conditioning of free-operant behavior. *Journal of the Experimental Analysis of Behavior, 34*(3), 297—304.

Holland, P. C. (2004). Relations between Pavlovian-instrumental transfer and reinforcer devaluation. *Journal of Experimental Psychology: Animal Behavior Processes, 30*(2), 104.

Holt, C. A., & Laury, S. K. (2005). Risk aversion and incentive effects: New data without order effects. *The American Economic Review, 95*(3), 902—904.

Keeton, C. P., Perry-Jenkins, M., & Sayer, A. G. (2008). Sense of control predicts depressive and anxious symptoms across the transition to parenthood. *Journal of Family Psychology, 22*(2), 212.

Keramati, M., Dezfouli, A., & Piray, P. (2011). Speed/accuracy trade-off between the habitual and the goal-directed processes. *PLoS Computational Biology,* 7(5), e1002055.

Leotti, L. A., & Delgado, M. R. (2011). The inherent reward of choice. *Psychological Science, 22*(10), 1310—1318.

Leotti, L. A., & Delgado, M. R. (2014). The value of exercising control over monetary gains and losses. *Psychological Science, 25*(2), 596—604.

Liljeholm, M., Dunne, S., & O'doherty, J. P. (2015). Differentiating neural systems mediating the acquisition vs. expression of goal-directed and habitual behavioral control. *European Journal of Neuroscience, 41*(10), 1358—1371.

Liljeholm, M., Molloy, C. J., & O'Doherty, J. P. (2012). Dissociable brain systems mediate vicarious learning of stimulus—response and action—outcome contingencies. *Journal of Neuroscience, 32*(29), 9878—9886.

Liljeholm, M., Tricomi, E., O'Doherty, J. P., & Balleine, B. W. (2011). Neural correlates of instrumental contingency learning: Differential effects of action—reward conjunction and disjunction. *Journal of Neuroscience, 31*(7), 2474—2480.

Liljeholm, M., Wang, S., Zhang, J., & O'Doherty, J. P. (2013). Neural correlates of the divergence of instrumental probability distributions. *Journal of Neuroscience, 33*(30), 12519—12527.

Lin, J. (1991). Divergence measures based on the Shannon entropy. *IEEE Transactions on Information Theory, 37*(1), 145—151.

Maeda, T., Kato, M., Muramatsu, T., Iwashita, S., Mimura, M., & Kashima, H. (2012). Aberrant sense of agency in patients with schizophrenia: Forward and backward over-attribution of temporal causality during intentional action. *Psychiatry Research, 198*(1), 1—6.

Martin, J. A., & Penn, D. L. (2002). Attributional style in schizophrenia: An investigation in outpatients with and without persecutory delusions. *Schizophrenia Bulletin, 28*(1), 131—141.

Mason, O., Claridge, G., & Jackson, M. (1995). New scales for the assessment of schizotypy. *Personality and Individual Differences, 18*(1), 7—13.

Mistry, P., & Liljeholm, M. (2016). Instrumental divergence and the value of control. *Scientific Reports, 6.*

Otto, A. R., Raio, C. M., Chiang, A., Phelps, E. A., & Daw, N. D. (2013). Working-memory capacity protects model-based learning from stress. *Proceedings of the National Academy of Sciences, 110*(52), 20941—20946.

Otto, A. R., Skatova, A., Madlon-Kay, S., & Daw, N. D. (2014). Cognitive control predicts use of model-based reinforcement learning. *Journal of Cognitive Neuroscience, 27*(2), 319—333.

Peng, L. W., Lee, S., Federman, E. B., Chase, G. A., Barta, P. E., & Pearlson, G. D. (1994). Decreased regional cortical gray matter volume in schizophrenia. *American Journal of Psychiatry, 151*(6), 843.

Peterson, C., & Seligman, M. E. (1984). Causal explanations as a risk factor for depression: Theory and evidence. *Psychological Review, 91*(3), 347.

Pol, H. E. H., Schnack, H. G., Mandl, R. C., van Haren, N. E., Koning, H., Collins, D. L., & Kahn, R. S. (2001). Focal gray matter density changes in schizophrenia. *Archives of General Psychiatry, 58*(12), 1118—1125.

Rangel, A., & Hare, T. (2010). Neural computations associated with goal-directed choice. *Current Opinion in Neurobiology, 20*(2), 262—270.

Schwartenbeck, P., FitzGerald, T. H., Mathys, C., Dolan, R., Kronbichler, M., & Friston, K. (2015). Evidence for surprise minimization over value maximization in choice behavior. *Scientific Reports, 5*.
Seligman, M. E., Abramson, L. Y., Semmel, A., & Von Baeyer, C. (1979). Depressive attributional style. *Journal of Abnormal Psychology, 88*(3), 242.
Shanks, D. R., & Dickinson, A. (1991). Instrumental judgment and performance under variations in action-outcome contingency and contiguity. *Memory & Cognition, 19*(4), 353–360.
Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction* (Vol. 1, No. 1). Cambridge: MIT Press.
Suzuki, S. (1999). Selection of forced-and free-choice by monkeys (*Macaca fascicularis*). *Perceptual and Motor Skills, 88*(1), 242–250.
Voss, M., Moore, J., Hauser, M., Gallinat, J., Heinz, A., & Haggard, P. (2010). Altered awareness of action in schizophrenia: A specific deficit in predicting action consequences. *Brain, 133*(10), 3104–3112.
Werner, J. D., Trapp, K., Wüstenberg, T., & Voss, M. (2014). Self-attribution bias during continuous action-effect monitoring in patients with schizophrenia. *Schizophrenia Research, 152*(1), 33–40.
Wunderlich, K., Dayan, P., & Dolan, R. J. (2012). Mapping value based planning and extensively trained choice in the human brain. *Nature Neuroscience, 15*(5), 786–791.
Wunderlich, K., Rangel, A., & O'Doherty, J. P. (2009). Neural computations underlying action-based decision making in the human brain. *Proceedings of the National Academy of Sciences, 106*(40), 17199–17204.
Zhou, S. Y., Suzuki, M., Takahashi, T., Hagino, H., Kawasaki, Y., Matsui, M., … Kurachi, M. (2007). Parietal lobe volume deficits in schizophrenia spectrum disorders. *Schizophrenia Research, 89*(1), 35–48.