Psychology of Habit

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Keywords

automaticity, dual-process models, goals, behavior change, model-free
learning

Abstract

As the proverbial creatures of habit, people tend to repeat the same behaviors
in recurring contexts. This review characterizes habits in terms of their cog-
nitive, motivational, and neurobiological properties. In so doing, we identify
three ways that habits interface with deliberate goal pursuit: First, habits
form as people pursue goals by repeating the same responses in a given con-
text. Second, as outlined in computational models, habits and deliberate goal
pursuit guide actions synergistically, although habits are the efficient, default
mode of response. Third, people tend to infer from the frequency of habit
performance that the behavior must have been intended. We conclude by
applying insights from habit research to understand stress and addiction as
well as the design of effective interventions to change health and consumer
behaviors.

Contents

INTRODUCTION

The yin and yang of the history of habits is closely tied to broader trends in the history of psychology. William James's (1890) view that "habit covers a very large part of life," necessitated that we "define clearly just what its limits are" (p. 104). Psychology complied, and the habit construct acquired specific meanings in the behaviorist traditions of Thorndike's (1898) law of effect, Hull's (1943) formalized drive theory, and Skinner's (1938) operant conditioning. However, these reinforcement-based models of habit were soon supplanted as the field embraced more purposive and cognitive perspectives. To Tolman (1948), repeated behaviors reflected learning of internal representations and maps, and Miller et al. (1960) argued that habits be replaced with information-processing mechanisms of goal pursuit. Accordingly, cognitive psychology and decision-making research in the 1960s and 70s developed largely separately from research on habit.

    More recent theories have captured the complexity of action control and enabled integration of these opposing conceptualizations. The concept of automaticity (Shiffrin & Schneider 1977) and theories of dual information processing (Wason & Evans 1975) provided frameworks inclusive of habits and thoughtful decision making. Through procedural memory, habits could be cognitively represented as distinct from other types of implicit processes as well as from explicit, declarative memories (Squire & Zola-Morgan 1991). Reinforcement learning (RL) research with animals identified a behavioral criterion for detecting habit performance, involving insensitivity to changes in rewarding outcomes (Dickinson 1985), and neuroscience began to identify the brain regions and circuits involved in habitual behavior (Graybiel 1998). Social-cognitive approaches outlined a variety of ways in which habits interface with goals (Verplanken & Aarts 1999, Ouellette & Wood 1998), and computational models included goal pursuit and prospective planning as

well as habit-like mechanisms of stimulus-driven or model-free action control (Cooper et al. 2014, Daw et al. 2005). Empirical fuel for the study of habit was provided by evidence of the high levels of repetition in daily activities (Khare & Inman 2006, Wood et al. 2002). Further framing these developments is the reading public's interest in understanding their own habits (e.g., Rubin 2015).

In this article, we take stock of the fast-growing research on habits. Our review is necessarily wide reaching, covering a variety of behavioral domains, cognitive tasks, and neuroscientific findings. We also consider animal learning research when relevant, given that habit learning mechanisms are largely conserved across mammalian species and do not appear to be degraded in humans or replaced by higher cortical functions (Bayley et al. 2005). Across these diverse research paradigms, the common elements are habit learning through repeated responding so as to form context-response associations in memory, and automated habit performance that is relatively insensitive to changes in the value or contingency of response outcomes. As we explain, these definitions of habit learning and performance capture the cognitive and neural mechanisms involved in habit memory and are reflected in characteristic patterns in habitual responding.

The schematic in **Figure 1** provides a framework for this review by depicting three ways in which habits interface with goals to guide behavior. Goals energize and direct action by defining a desired end state. In our three-pronged model, habits and goals interact through habit formation, habit performance, and inferences about the causes of behavior. First, goals influence habit formation by initially motivating people to repeat actions and to expose themselves to performance contexts (see Habit Formation section). This is illustrated by the arrows from goal system to context cues and habitual response in **Figure 1**. Once habits form, context cues come to automatically activate the habit representation in memory (see Habit Automaticity section). Second, people act on the habit in mind as well as on their prevailing goals by tailoring their behavior to the current circumstances (see Computational Models section). External factors such as stress and distraction influence the impact of these two processes by reducing the motivation or ability to deliberately pursue goals and increasing reliance on habits (see section Factors that Shift the Balance Between Habits and Goals section). As outlined in dual-process frameworks, habits provide a sort of default response unless people are sufficiently motivated and able to tailor their behavior to current circumstances. Finally, people make inferences about their goals based on observing their own frequent behavior, as reflected by the double-headed arrow in **Figure 1** between the habitual response and the goal system (see Inferences about the Causes of Habit Performance section).
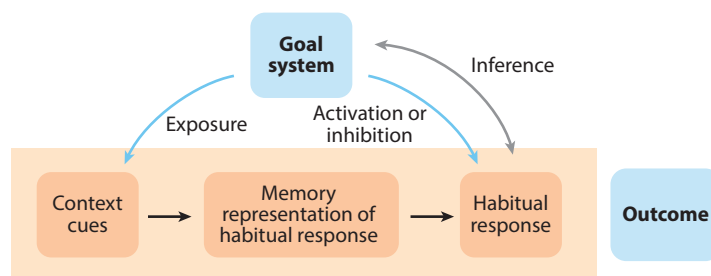
Figure 1

Schematic of three ways in which habits interface with deliberate goal pursuit: through initial repetition and exposure to contexts during habit formation (illustrated by the arrows from goal system to context cues and habitual response), through activation or inhibition of the habitual response, and through inferences about the probable causes of habit responding (reflected by the double-headed arrow between habitual response and goal system).

To conclude the review, we apply insights from basic research on habit to understand stress and addiction and to design successful behavior-change interventions (see Changing Habits section).

HABIT AUTOMATICITY

The terms habit and automaticity are sometimes used interchangeably. Like other automatic responses, habits are activated in memory in an autonomous fashion without requiring executive control (Evans & Stanovich 2013). Habits, however, are not synonymous with automaticity but are best understood as learned automatic responses with specific features (Wood et al. 2014). Two defining features of habit automaticity are (*a*) activation by recurring context cues and (*b*) insensitivity to short-term changes in goals (a.k.a., not goal dependent), including changes in the value of response outcomes and the response-outcome contingency. Additional features that apply to most habitual responses include speed and efficiency, limited thought, rigidity, and integration of sequences of responses that can be executed as a unit (Seger & Spiering 2011, Smith & Graybiel 2013). However, each of these additional features may not be assessed in all habit research paradigms. Instrumental learning studies, for example, often do not evaluate response speed, whereas learning of motor sequences in cognitive-experimental research is assessed primarily via changes in response latency.

Habits differ from other automatic, implicit processes including priming, classical conditioning, and nonassociative learning (Evans & Stanovich 2013, Squire & Zola-Morgan 1991). For example, the priming of goals, attitudes, or concepts can activate a range of responses, not only the repetition of a particular well-learned response (see Wood et al. 2014). Even strongly desired goals that stably characterize people's motives do not necessarily yield stability in the particular means of goal pursuit. In contrast, habit automaticity applies to a specific response. Furthermore, unlike habits, automated goals (e.g., implementation intentions) influence behavior primarily to the extent that they are consistent with people's explicit motivations (Sheeran et al. 2005).

Automatic Cuing of Habits

A variety of cues might trigger habit performance, including aspects of physical environments, other people, and preceding actions in a sequence. Once habits form, perception of the relevant context cues automatically activates the mental representation of the habitual response. Exposure to cues might be deliberate, as when sitting at a computer in order to activate thoughts of work. Or exposure can be inadvertent, as when a chance sighting of a fast-food outlet activates thoughts of eating. We assume that the memory representation of a habit response is cognitively richer than a mere motor program that controls response execution. Given that human cognition is based on integrated sensorimotor units (Hommel 2009), a habitual response will be represented in terms of response features as well as perceptual features. Specifically, the sensory feedback while making a response, which gives rise to the experience of performing the action, is included in the mental representation. As a consequence, a habit cue not only triggers a motor program, it also activates a multimodal representation, or thought, of the habitual response. Consistent with this view, Neal et al. (2012) found that runners with strong running habits automatically brought to mind thoughts of running and jogging when exposed to words designating the physical locations in which they typically ran.

Once habitual responses are activated, people can act on the response in mind without making a decision to do so. That is, habit performance follows relatively directly from the perception of context cues and thoughts about the behavior, reflecting the tight linkage between an internal action representation and the action itself (James 1890). For example, when students who

frequently went to the sports stadium on campus were incidentally exposed to an image of the stadium, they raised their voices as they would habitually in that context, despite no change in their motivation to speak loudly (Neal et al. 2012). Also, in a study conducted in a local cinema, participants with stronger habits to eat popcorn at the movies consumed more than those with weak habits, even when they disliked the popcorn because it was stale and unpalatable (Neal et al. 2011). However, when in a campus meeting room watching music videos, participants with strong cinema-popcorn eating habits were guided by their preferences and ate little stale popcorn.

Habit performance is typified by the insensitivity to outcomes apparent in speaking loudly in a quiet laboratory setting and eating popcorn despite disliking it. This insensitivity has been demonstrated directly in instrumental learning experiments in which participants were first trained extensively to choose a reward to a certain image cue (e.g., Tricomi et al. 2009). Participants then ate as much of the reward as they desired, so that they did not want any more of that specific food. Nonetheless, when tested again, extensively trained participants in this paradigm continued to make the habitual but unwanted choice to the associated image (see also Hogarth et al. 2012b, Schwabe & Wolf 2010).

Triandis's (1977) early work on behavior prediction sparked social psychologists' interest in the idea that repeated behavior becomes more habitual and less dependent on goal pursuit. In prediction studies, behavioral intentions and habit strength (usually operationalized as frequency of past performance) are used to predict future performance. In a meta-analysis of 64 such studies, Ouellette & Wood (1998) found that intentions were stronger predictors of actions that were performed only occasionally (e.g., getting flu shots) than actions that could be repeated more regularly (e.g., wearing seat belts). Actions performed regularly apparently became habitual and persisted with little guidance from intentions (see also Gardner et al. 2011). In addition, habits and intentions interact in guiding daily variations in behavior. For example, on days when participants' intentions to engage in physical activity were weaker than usual, they fell back on their exercise habits and worked out only to the extent that exercise was habitual (Rebar et al. 2014). Also, in a longitudinal test, habit strength to donate blood determined the relation between intentions and actual donations (P. Sheeran, G. Godin, M. Conner, and M. Germain, unpublished data). That is, for participants with weak donation habits, increasingly favorable intentions predicted a greater number of future donations. However, as habit strength increased, the predictive power of intentions diminished, and participants with the strongest habits simply repeated their past donations without input from intentions.

When acting out of habit, the ready response in mind reduces deliberation and narrows focus even when some explicit decision making is required. In a multiattribute choice task involving a series of travel mode decisions, participants with stronger habits to ride a bike or drive their car conducted less extensive information searches, considered fewer action alternatives, and biased the searches toward their habitual choice (Aarts et al. 1997; see also Betsch et al. 2001). Experimentally enhancing attention to the decision process temporarily increased alternative choices, but the habitual choice reemerged with continued decisions (Verplanken et al. 1997). These results may in part reflect that the repeated activation of one response in a context reduces the cognitive accessibility of alternatives (Danner et al. 2007). Essentially, people with strong habits process information in ways that reduce the likelihood that they will consider acting otherwise.

Habit Automaticity and Deliberation About Action

Dual-process theories of decision making and judgment outline the mechanisms that lead people to respond automatically or to engage in deliberate information processing that draws on the limited-capacity resource of working memory (Evans & Stanovich 2013). From this view, people

often act habitually in the interests of efficiency (Wood et al. 2014). When motivated and able to engage in deliberate goal pursuit, however, they might identify desired outcomes, set and initiate behavioral intentions, end actions, and evaluate outcomes (Gollwitzer & Brandstätter 1997).

Dual-process models in psychology often specify that automatic and deliberate systems interact through a default-interventionist architecture (Evans & Stanovich 2013) so that responses are largely habitual unless the deliberative system intervenes to impose an alternative. In contrast, reinforcement-learning computational models of routine behavior and decision making (see Computational Models section) often invoke the less psychologically plausible parallel-competitive form of dual-process architecture, in which planning proceeds in parallel with habitual control. As Evans & Stanovich (2013) point out, parallel processing assumes that a costly central executive is almost continuously ready to be engaged in planning and deliberation. More recently, some computational models have adapted a more default interventionist approach in which planning intervenes to alter habits only when necessary (e.g., Pezzulo et al. 2013). It is useful to note that, although we invoke the dual-process framework in this review, action control is influenced by more than two processes, including automated goal pursuit (Sheeran et al. 2005) as well as Pavlovian conditioning of incentive motivation (Balleine & O'Doherty 2010).

In summary, perception of habit cues automatically activates habit representations, and people typically carry out the habit in mind. Thus, behavior prediction studies reveal that people often act out of habit, even when it is in conflict with their intentions. In dual-process models depicting the ways that habits integrate with goals in guiding behavior, habits are a ready default unless people are motivated and able to intervene and engage in more deliberate goal pursuit.

HABIT FORMATION

Given that everyday habits develop as people go about pursuing life goals, habit formation is closely intertwined with goal pursuit. Nonetheless, an implication of the basic context-response mechanism underlying habits is that behavior becomes less responsive to current goals and planning as habit associations strengthen.

Habits develop through instrumental learning and build on the fundamental principle that rewarded responses are repeated (Thorndike 1898). When repeatedly pursuing a goal such as making coffee, people experience covariations between context cues (e.g., coffee filter) and actions (e.g., measure grounds) that lead to goal attainment. Daily life is full of such repetition. In experience-sampling research in which people recorded once per hour what they were thinking, feeling, and doing, about 43% of actions were performed almost daily and usually in the same context (Wood et al. 2002; see also Khare & Inman 2006). Particular actions, such as types of food eaten, also tend to be performed in particular physical locations (Liu et al. 2015). Typically, the learning of context-response associations is an unintended consequence of this repetition. Suggestive of this automaticity, participants in Wood et al.'s (2002) study often reported that they did not think about repeated behaviors during performance.

Associative and Reward Mechanisms in Habit Learning

Habits strengthen through associative and reward-learning mechanisms that capture the slow, incremental nature of habit formation. With each repetition, small changes occur in the cognitive and neural mechanisms associated with procedural memory. Through Hebbian learning of repeated connections, cognitive associations between context cues and a response are strengthened gradually so that people are prepared to repeat performance when the context cues are encountered again (called direct cuing by Wood & Neal 2007).

The strength of context-response associations is further modulated by the reward following the response. At a neural level, midbrain dopamine systems support this reinforcement process. By signaling reward prediction errors, or the discrepancy between an anticipated and actual reward, a phasic dopamine response acts as a teaching signal for habit learning in the striatum (Balleine & O'Doherty 2010). Specifically, the dopaminergic signal that is triggered by an unexpected change in reward magnitude works retroactively to stamp in associations between the still-active memory traces of the response and the cues in the performance context (Wise 2004). Thus, dopamine signals promote habit learning as people initially repeat responses to a reward, but the signals become less active with repetition, as the reward recurs.

In computational RL models, habit formation is conceptualized as the learning of value signals that represent the expected future rewards for the different response options in a given context and provide the basis for selecting an action (see Computational Models section). Value-based selection of habitual responses can be can be regarded as a form of motivated cuing (Wood & Neal 2007).

Another way in which habitual responding continues to be influenced by motivational processes is through context cues that have become associated with the reward that follows an action. As learned predictors of reward, such Pavlovian context cues can cause the habitual response to be performed with increased vigor (Balleine & O'Doherty 2010). Of note, the motivational effect of such Pavlovian predictors of rewarding outcomes is distinct from the motivational value of the outcome itself. Holland (2004), for example, found that responses extensively trained into habits were insensitive to changes in outcome value but continued to be influenced by reward-related cues.

A standard finding from animal learning is that habits develop most readily when rewards are provided on interval schedules, meaning that responses are rewarded only after a time has elapsed. Such rewards mimic natural resources that are replenished over time. With these schedules, changes in response rate during the time interval do not change the amount of reward delivered, reducing the experience of instrumental contingency between the response and the reward (Dickinson 1985). Thus, interval rewards likely promote habit learning because context-response associations can form without including a representation of the goal or outcome of the action.

As a caveat to the principle that habits form from repetition, habits do not always emerge with complex tasks in which different response choices lead to different rewards. In animal research, even after extensive training at a task involving a lever press (yielding sucrose) or chain pull (yielding a food pellet), rats failed to form habits—they continued to be sensitive to reward value and ceased responding for one of these rewards after it had been paired with a toxin (Colwill & Rescorla 1985). Perhaps in an analogous fashion, decision making in humans impedes habit formation. In a repeated sequential choice task, participants failed to form habits to the extent that they spontaneously used a planning strategy and based their choices on the value and probability of response outcomes (Gillan et al. 2015). Similarly, habit formation was hindered when an instrumental task promoted planning compared with mapping of responses to cues (Liljeholm et al. 2015). It appears, then, that deliberative decision making is protective against habit formation even when people respond repeatedly to particular cues.

In summary, habits are likely to form from responses repeated contiguously with context cues, especially when responses are rewarded on an interval schedule. Through the activation of dopamine systems, habits form that are insensitive to current shifts in reward value and structure. However, planning and making deliberate choices during responding can hinder habit formation.

Measures of Habit Strength

Habitization is a process, with no clear demarcation point when strong habits have formed. Nonetheless, instrumental learning tasks provide a clear behavioral criterion. That is, habits have

formed when participants continue to repeat a well-practiced response after the reward has been reduced in value (e.g., for food rewards, after consuming to satiety) or is no longer tied to the response (Dickinson 1985). In these paradigms, habitual responding is evaluated during a subsequent extinction phase (rewards withheld) in order to preclude additional learning based on the changed reward values.

Behavioral indicators of habit strength are captured in a variety of experimental paradigms beyond the simple motor responses often thought emblematic of habits. Habit strength has been manipulated in experimental paradigms involving word-association tasks (Hay & Jacoby 1996, Quinn et al. 2010), choice tasks involving pictorial and other judgment stimuli (de Wit et al. 2009, Gillan et al. 2015), two-stage decision-making tasks (Daw et al. 2011), and problem-solving tasks such as tower building (Patsenko & Altmann 2010). Strong habits also have been formed as humans repeatedly navigate through virtual mazes (Marchette et al. 2011) and rats through actual mazes (Packard & Goodman 2013). Echoing insensitivity to reward, strong habits in these paradigms often emerge as errors, reflecting persistent responding despite task changes in the correct, rewarding outcome. Habits also emerge as chunked responses into a unit (Dezfouli & Balleine 2013, Graybiel 1998), which is related to the performance gains (reduced response time, increased accuracy) in many sequential learning tasks (e.g., Lungu et al. 2014). In addition, eye-tracking measures have been used to capture visual attention to task structures triggering habitual responses (Patsenko & Altmann 2010).

The strength of everyday habits is typically assessed from people's self-reports. One method is to combine self-reported ratings of behavioral frequency with ratings of the stability of the performance context, reflecting the logic that habits represent the repeated pairing of responses and recurring context cues (Galla & Duckworth 2015, Wood & Neal 2009). Using an alternative approach, the Self-Report Habit Index estimates habit strength from a questionnaire measure of the experience of automaticity and frequency of past performance (Verplanken & Orbell 2003), which has further been streamlined to measure only automaticity (Gardner 2014, Gardner et al. 2012). However, as Labrecque & Wood (2015) noted, experienced automaticity measures often fail to assess triggering contexts and may capture automation more generally, as opposed to habit automaticity that guides performance with limited input from current intentions. However, these measures can successfully capture habit strength when triggering cues are present (P. Lin, W. Wood, and J. Monterosso, unpublished data). Perhaps the most valid assessments of everyday habit strength involve reaction time measures of the accessibility of the habitual response given exposure to associated context cues (e.g., Neal et al. 2012).

In summary, assessments of habit formation rest most importantly on evidence that responses are insensitive to changes in rewarding outcomes. Habit formation has been documented in a variety of laboratory tasks using a variety of behavioral assays. For everyday habits, self-report assessments can capture habit strength, although direct assessment of context-response associations is probably most effective.

COMPUTATIONAL MODELS

Computational models offer detailed accounts of the cognitive processes that support habit learning and performance. We selectively focus on models that incorporate habit-like control systems as well as deliberate goal pursuit. Instead of making the simplified assumption that a behavior is either goal directed or habitual, these models explore how adaptive behavior can emerge from the interplay of different models of action control. Competing ideas have been proposed about how the different action controllers work together to produce a response.

In Cooper et al.'s (2014) goal circuit (GC) model, goals structure the learning of habits and control their expression. The GC model is an artificial neural network composed of two interlinked

habit and goal subnetworks. The habit system, which was originally proposed by Botvinick & Plaut (2004), selects actions in a bottom-up manner based on the current stimulus environment and on internal feedback about the network's previous state. This response selection process is biased by input from the goal system. A habit develops gradually as the network repeats the same sequence of responses while learning to attain goals in a particular environment. Eventually, the habit system becomes capable of performing a sequence autonomously without goal input. In addition to guiding learning in the habit system, the goal network enables top-down control over habitual action sequences, as when a person deliberately overrides a habitual response.

Taatgen et al. (2008) developed a model within the ACT-R (adaptive control of thought–rational) cognitive architecture that shows how behavioral control shifts from an internal, declarative task representation to environmental cues when acquiring a new action routine. Initially, explicit task knowledge is used to control behavior in a goal-directed manner. With practice, explicit memory retrieval is gradually transformed into a process by which perceptual cues trigger the relevant action directly. This proceduralization of explicit knowledge accounts for performance improvements during skill learning. Additional learning is possible by combining stimulus-cued productions of sequences into a single new production. The creation of new, specialized knowledge structures or chunks that can be used more efficiently is a central element in cognitive theories of skill acquisition (Newell 1990).

In cognitive neuroscience, the prevalent theoretical perspective is that goal-directed actions and habits can be described by different classes of RL (Daw et al. 2005, Dolan & Dayan 2013). Goal-directed, or model-based, learning is a computationally demanding process of mental simulation and planning. Using this approach, an agent computes on the fly which action maximizes long-run cumulative reward. Habit formation, in contrast, relies on model-free RL involving trial-and-error learning to estimate and store the long-run values of actions that are available in the different states or contexts. Actions are then chosen based on the stored or cached action values, reflecting predictions about future reward. Model-free control lacks the flexibility of model-based learning because short-term changes in the reward value of an action outcome have only limited effect on the cached value. Thus, model-free RL theoretically captures a key property of habits—insensitivity to changes in reward. Both types of learning are driven by prediction errors, with model-based learning capturing the discrepancy between the current state and the expected one and model-free learning capturing the difference between predicted and experienced reward.

In an initial dual-system RL model, Daw et al. (2005) assumed a competitive, winner-take-all mechanism in which the habit system or the goal system gained control over action, depending on which system provided the more reliable estimates of action values. However, subsequent investigations favor a more dynamic integration in which both systems contribute to the computation of action values according to their relative reliabilities (Lee et al. 2014). A related proposal involves Bayesian model averaging that takes into account prediction accuracy and model complexity. In this view, with experience, goal-directed actions are replaced by habits because the habit system becomes increasingly reliable and favored over the computationally more complex goal-directed system (FitzGerald et al. 2014). Furthermore, is it likely that model-based judgments are implemented only selectively, given the psychological costs of planning (see Habit and Deliberation section)? In recognition, a number of contingent RL systems engage model-based processing conditional on trade-offs between accuracy and efficiency (Keramati et al. 2011, Pezzulo et al. 2013).

Beyond integrating independently computed action values, some RL models assume a direct influence of goal values on habit learning. For example, in Gershman et al.'s (2014) two-step decision task, participants changed their choice preferences in the first task step after independently learning about second-step reward contingencies. To account for this finding, Gershman and colleagues argued that the model-based system simulated a complete two-step decision process, and

the model-free system learned from the simulations. Similarly, Pezzulo et al. (2013) proposed that model-based planning can update and improve the value estimates of the model-free system. By enabling goals to influence the action values represented in habit learning, these models promote the formation of habits compatible with goals.

The RL approach can account not only for the insensitivity of habits to changes in reward value but also for the chunking feature of habit automaticity. Theories of hierarchical RL show that it can be advantageous to concatenate individual actions and treat the sequence as a single response unit or chunk (Botvinick & Weinstein 2014) because the faster responding enabled by chunking can lead to greater average reward (Keramati et al. 2011). The chunked units could be deployed in a goal-directed (Dezfouli & Balleine 2012) or model-free manner on the basis of the reward history (Botvinick et al. 2009).

Questions remain, however, about the appropriateness of equating model-free learning with habit processes. Dezfouli & Balleine's (2012) proposal that habits are action chunks that are acquired and controlled through model-based processes marks a radical departure from the common RL assumption that habits are the result of model-free learning. Even more significant, individual-difference studies have reported that the strength of model-free learning was unrelated to habit formation and insensitivity to the value of the task outcome (Friedel et al. 2014, Gillan et al. 2015). Instead, outcome insensitivity was greater among participants evidencing little model-based learning. It is possible that the standard two-stage RL decision task does not capture the process that produces outcome-insensitive habits, perhaps because participants have to choose between multiple outcomes with varying reward rates (see discussion in the Associative and Reward Mechanisms in Habit Learning section). Thus, model-free learning in these tasks might reflect other stimulus-driven strategies such as simple decision heuristics instead of habits. Future research on model-free processes may need to develop new experimental tasks to better capture habits.

In summary, habits form as a product of repeated behaviors in the service of goal pursuit. Learning in the habit system may proceed independently or be guided by the goal system. Recent theories suggest that rather than being independent action controllers, habit and goal systems integrate in ways that reflect the reliability of each system and the costs of planning. In some contingent RL models, the habit system serves as an efficient default, and people plan only when motivated and able.

NEUROBIOLOGY OF HABITS

From a dual-system perspective, a fundamental objective is to identify brain regions whose activity is uniquely associated with habitual and goal-directed behavior, respectively. Current neuroscientific research is guided, to an increasing extent, by the computational RL models that we discussed in the previous section. Thanks to the rapid advancement of functional neuroimaging with human subjects, it is now possible to relate computational dual-process models to brain functioning at increasingly fine-grained levels of analysis. The emerging picture is one of a neurocognitive system that integrates the computations of partially overlapping neural systems of habitual and goal-directed control.

Neural Systems Associated with Habits

Research conducted with rodents, monkeys, and humans has provided converging evidence that habitual and goal-directed behaviors are mediated by neural circuits that link cortical brain areas and the basal ganglia (BG), a collection of subcortical nuclei. These circuits are organized as anatomically separate reentrant loops, two of which are essential for deliberate and habitual responding (Burton et al. 2015, Yin & Knowlton 2006). The associative cortico-BG loop supports

working memory functions and goal-directed actions and links the prefrontal cortex (PFC) with two striatal BG regions, the caudate nucleus and the anterior putamen. The sensorimotor loop underlies automatic, habitual behaviors and connects the somatosensory and motor cortex with the medial and posterior putamen. Though anatomically separate, the two loops can interact, for example, through spiraling dopaminergic connectivity (Haber et al. 2000).

Animal learning studies have demonstrated the importance of the sensorimotor loop for habitual responding. Rats do not acquire a lever-pressing habit when their dorsolateral striatum (DLS), the equivalent of the primate putamen, is lesioned prior to lever-press training for sucrose. Even after extended training, these rats continued to be goal directed and pressed the lever less frequently when sucrose was devalued (Yin et al. 2004). Furthermore, when the DLS was inactivated pharmacologically after a lever-pressing habit was acquired, outcome sensitivity was reinstated (Yin et al. 2006).

Suggesting that the DLS is involved in the chunking of individual actions into a sequence, electrical recordings from neurons in the DLS of rats exhibited a task-bracketing pattern of activity during habitual runs through a maze—high neuronal activity at the beginning and end of a run, with lower activity in-between. Task bracketing emerged when the learned behavior was still goal directed (Smith & Graybiel 2013), which indicates that habits develop in parallel with goal-directed learning but do not influence overt behavior early in training. By contrast, when goal-directed control is abolished by lesioning associated brain regions such as the rodent posterior dorsomedial striatum (DMS, corresponding to the caudate nucleus in primates) or the prelimbic medial PFC, behavior immediately comes under habitual control (Killcross & Coutureau 2003, Yin et al. 2005).

Neuroimaging research with human participants implicates similar networks of brain regions. Practicing sequences of finger movements for days or weeks decreased brain activation in areas associated with goal-directed control [e.g., premotor and prefrontal cortical areas, anterior cingulate cortex (ACC), and associative BG territories] and increased activation in the sensorimotor network, including the putamen (e.g., Lehéricy et al. 2005, Steele & Penhune 2010). Participants who developed a lever-pressing habit for potato chips and candy over three days of training showed similar increases in activity in the sensorimotor striatum (posterior putamen) both within practice days as well as across days (Tricomi et al. 2009). Neuroimaging studies of motor sequence learning further confirmed the role of the sensorimotor striatum in chunk formation, along with a frontoparietal network and the mediotemporal lobes (Lungu et al. 2014).

The sensorimotor loop is critical for habit learning, and an extended network of brain regions modulates its activity. Motivational influences on habit acquisition are mediated by ascending dopamine projections from the substantia nigra pars compacta to the dorsal striatum that modulate habit plasticity at corticostriatal synapses (Balleine & O'Doherty 2010). Lesioning this nigrostriatal pathway in rats disrupted habit formation (Faure et al. 2005). Habit acquisition also was impeded by lesions of the amygdala central nucleus, most likely due to its effect on substantia nigra pars compacta function (Lingawi & Balleine 2012). Finally, rodents' infralimbic cortex, a medial PFC region, directly participates in the formation of a habit and is required for its expression (Killcross & Coutureau 2003, Smith & Graybiel 2013).

Whether the sensorimotor loop is responsible for long-term habit storage remains unclear. After six months of practicing sequences of joystick movements, monkeys that had their sensorimotor loop disrupted pharmacologically were not impaired in the expression of sequence knowledge and still executed overlearned sequences faster and more accurately than random control sequences (Desmurget & Turner 2010). One explanation is that, with extensive practice, habit learning is consolidated in cortical brain areas (Atallah et al. 2007). This possibility fits Penhune & Steele's (2012) conclusion that long-term representations of learned skills are encoded in a network of

motor cortical regions. In their research, delayed recall of a motor sequence engaged not the BG but rather cortical regions (primary motor and premotor cortices and parietal lobe). This idea is supported further by the finding that participants who practiced motor sequences for more than six weeks showed, late in training, neural specialization in cortical motor areas [primary motor and premotor cortices and the supplementary motor area (SMA)] (Wymbs & Grafton 2014).

In summary, converging evidence implicates the sensorimotor cortico-BG loop as the core neural substrate of habit learning and performance. Whether the BG is also required for the long-term retention of habits is a matter of current debate.

Neural Systems that Integrate Habit and Goal-Directed Action Control

Based on computational RL theory, a stream of neuroimaging research has evaluated performance in sequential decision tasks that elicit both habit-based (model-free) learning and prospective planning about outcomes (model based). The results are broadly consistent with the mapping of habitual and goal-directed control onto the associative and sensorimotor cortico-BG loops. For example, Wunderlich et al. (2012) related activity in the posterior putamen to cached action values (habits) that were acquired through extensive training, and activity in the anterior caudate nucleus was related to values used in model-based planning. Similarly, Lee et al. (2014) reported that the posterior putamen, SMA, dorsomedial PFC, and dorsolateral PFC encoded model-free action values, whereas model-based values were associated with activity in orbitofrontal cortex (OFC) and medial PFC as well as the ACC (see also de Wit et al. 2009, Valentin et al. 2007).

Recent dual-system RL models propose that response selection is based on action values represented in ventromedial prefrontal cortex (vmPFC) that are jointly determined by a model-free (habit) and prospective planning controllers (e.g., Daw et al. 2011). This integration of model-based and model-free value signals is thought to be conducted by an arbitrator associated with activity in the inferior lateral PFC, frontopolar cortex, and ACC (Lee et al. 2014). How exactly such an arbitrator regulates the contribution of each system is still largely unknown. According to one analysis, shifts in response strategy are achieved primarily by strengthening or inhibiting the influence of the model-free habit system (Lee et al. 2014). Other findings suggest dynamic changes in both the habit system and the goal system (Gremel & Costa 2013).

Consistent with the idea that habits develop as people pursue goals, recent evidence suggests that multiple brain regions participate in both goal-directed and habitual control. For example, Lee et al. (2014) found with the multi-step decision task that two regions, the SMA and dmPFC, represented both model-free and model-based values. Similarly, Gremel & Costa (2013) trained rats to lever press for sucrose using either a habitual or a goal-directed strategy. They reported that a large proportion of neurons in DLS, DMS, and OFC participated in both habitual and goal-directed responding, and that the relative engagement of neurons in these areas depended on the current response strategy.

In summary, research guided by RL theory has identified the neural substrates of model-based (goal-directed) and model-free (habitual) control. These neural systems are partially overlapping, and their computations are integrated by brain regions that regulate the relative influence of the two modes of behavioral control.

FACTORS THAT SHIFT THE BALANCE BETWEEN HABITS AND DELIBERATE GOAL PURSUIT

Given the cognitive and neural features that differentiate habitual responding from more deliberate pursuit of goals, action control proceeds by balancing these and other processes (e.g., Pavlovian

HABIT SLIPS

Habit slips, or errors of inadvertent habit performance, occur primarily when an intended action and a habit share a performance context or some action component (Norman 1981). In daily life, people appear to slip up by performing unwanted habits about six times a week, especially when their attention is diverted from the task at hand (Reason 1979). For example, habit slips underlie errors in responding to innocent-appearing email phishing attacks (Vishwanath 2015). In laboratory tests, habits were most likely to be performed inadvertently when goal-directed control was taxed by, for example, advanced age or performing a secondary task (e.g., de Wit et al. 2014, Ruh et al. 2010).

Moving beyond the truism that people make errors when not attending to what they are doing, research has identified several sources of habit slips. Slips arising from failures in planning reflect limits in motivation or knowledge about completion of task goals, and they are most likely at decision points such as the end-of-task subroutines (Norman 1981, Reason 1979). However, habit slips also emerge from failures in automated, habitual guides to performance, as when degraded or forgotten representations of task context occur within a sequence of well-learned actions (Botvinick & Bylsma 2005). In still another analysis, habit slips arise from normal processing, especially open-loop action control in which habits are executed ballistically once they are launched, even when they are not the optimal response (Dezfouli et al. 2014, Orbell & Verplanken 2010). Thus, habit slips reflect failures to select the correct action through top-down control or bottom-up activation as well as ballistic habit performance.

conditioning; de Wit & Dickinson 2009). Tipping the balance between habits and goal pursuit are factors such as distraction (see Habit Slips sidebar), time pressure, limited task ability, or limited willpower (for a review, see Wood et al. 2014). These factors drive action control by pitting efficiency in processing against more effortful reliable processing (Evans & Stanovich 2013). That is, people act on strong habits when they lack the ability and motivation to engage the central executive in deliberation or, in RL terminology, when pressured by the time costs of model-based planning.

Considerable research reveals increased habit performance with impaired executive functioning. For example, when willpower was reduced by previously performing a taxing decision-making task, participants did not tailor their responses to their current circumstances but instead fell back on strongly habitual choices (Neal et al. 2013, Vohs et al. 2005). Also, when distracted by performing a demanding task, participants completing a categorization task increased the use of stimulus-response strategies over rule-based ones (Foerde et al. 2006), and participants completing a multistep decision task increased model-free responding (Otto et al. 2013a). Furthermore, in individual-difference paradigms, older adults and those with lower cognitive-control abilities were less able to leverage higher-order goal representations for model-based responding in order to overcome habitual, model-free solutions to a variety of tasks (de Wit et al. 2014, Otto et al. 2015). In like manner, participants possessing low spatial perspective-taking ability, after practicing navigating a maze, used more habitual and less goal-directed navigation strategies (Marchette et al. 2011).

Stress and drug addiction are of particular interest because of the multiple routes by which they tip the balance toward habits and away from deliberate decision making. As we explain in the next sections, these factors not only impede executive processes but also perhaps promote habit learning.

Stress

Acute as well as chronic stress can increase people's reliance on habits (Schwabe & Wolf 2013). For example, participants exposed to a combination of physical and psychosocial stressors (immersing a

hand into ice water while being monitored by a stranger and videotaped) after instrumental learning acted more habitually and were less sensitive to changes in the value of task rewards (Schwabe & Wolf 2010). This stress-induced shift toward habits is due in part to stress impeding deliberate action control. At the neural level, the shift toward habitual behavior was accompanied by decreased activity in OFC and medial PFC, brain regions associated with goal-directed learning (Schwabe et al. 2012). In sequential decision-making tasks, acute stress selectively attenuated deliberate, model-based control and promoted habit performance in vulnerable participants—those with low working-memory capacity (Otto et al. 2013b) or high levels of chronic stress (Radenbach et al. 2015). Similarly, in a study of visual classification learning, stressed participants were biased toward relying on a habit-linked procedural learning strategy at the expense of explicit learning (Schwabe & Wolf 2012). These results could reflect simply the breakdown of higher-order decision-making functions under stress, or stress could lead to a shift in the allocation of cognitive resources so that people fall back on habits and other strategies to prevent unreliable performance. From an RL perspective, stress shifts the balance toward habits over lengthy planning by increasing experienced time pressure (Doll et al. 2012).

Along with impeding deliberate thought, stress also might promote habit acquisition. Research with rodents suggests that stress can, under specific conditions, facilitate habit learning through mechanisms associated with dorsolateral striatal function (Dias-Ferreira et al. 2009). In humans, however, stress does not clearly affect habit formation. To isolate stress effects on habit learning, stress is induced before training, and learning is assessed after acute stress effects have dissipated so that these do not affect performance. Administering stress hormones led to improved learning in a simple stimulus-response task but had no effect on habit learning in a virtual radial maze (Guenzel et al. 2014a). Furthermore, a combination of pretraining physical and psychosocial stressors actually impaired habitual performance at maze navigation, albeit only in male participants (Guenzel et al. 2014b).

In summary, neurophysiological responses to stress increase habitual responding by impeding deliberate action control and, potentially, by promoting habit formation. More generally, stress research highlights the benefits of habits for rescuing performance. In support of this functional role, stressed participants' task performance was impaired to the extent that they attempted to engage goal-directed neural systems (Schwabe & Wolf 2013). Given the ready acquisition and performance of habits, they provide a useful default when threat and pressure derail more thoughtful responding.

Addiction

From a habit perspective, the path to drug addiction involves not a pathological motivation for drugs but rather a shift from goal-directed to habitual drug seeking and consumption (Everitt 2014, Hogarth et al. 2013). Initial drug seeking is voluntary and reflects the hedonic value of the drug. Through instrumental learning with drug rewards, context cues rapidly become associated with drug use. In addition, Pavlovian mechanisms contribute to the want for drugs and for cue-evoked cravings (Berridge 2007). These various learning mechanisms are involved in the cues that come to trigger drug seeking and consumption independently of the drug outcome, much as people repeat habits with limited sensitivity to goals and outcomes (Zapata et al. 2010). Phenomenologically, the addict no longer likes the drug yet uses it compulsively, often despite intentions to quit. Drug-outcome insensitivity is promoted further as repeated exposures build tolerance to rewarding drug effects.

Drug use promotes habit formation in part by impairing goal-directed control. In illustration, study participants who had consumed alcohol responded habitually and continued to choose

chocolate in a repeated food-choice task despite having just eaten three chocolate bars (Hogarth et al. 2012a). Comparable findings have emerged with chronic addicts abstinent at test. For example, participants who were obese, obsessive-compulsive, or dependent on methamphetamine (abstinent at test) showed compromised goal-directed learning at a decision-making task, along with a maladaptive reliance on habits (Voon et al. 2015). Furthermore, these responses in chronic addicts were associated with neural markers of lower gray matter volumes in the caudate, medial OFC, and lateral PFC. Also, alcohol-dependent participants responded habitually after rewards had been devalued in an associative learning task, and greater reliance on habits was associated with reduced engagement of brain areas implicated in goal-directed action (vmPFC) and increased engagement of areas implicated in habit learning (posterior putamen; Sjoerds et al. 2013). Even when not under drug influence, simply being in the presence of cues repeatedly associated with drug exposure can disrupt goal-directed responding (Ostlund et al. 2010). In general, goal-directed impairments increasingly narrow addicts' behavioral repertoires onto drug habits by restricting their capacity for intentionally selecting alternative actions.

Drug use also promotes habit responding through neurobiological processes that sensitize users to the incentive properties of drugs. Drug rewards appear to engage habits more rapidly than other reinforcers (see review in Everitt 2014). Stimulants in particular accelerate and consolidate the development of drug use habits, speeding the neural shifts from associative to sensorimotor areas typically found with habit formation. The accelerated formation of habits hastens the transition from initial or occasional user to addict.

In summary, drug exposure hijacks the habit learning system by exerting a continuous pressure in favor of habitual, context-driven behavior and away from the evaluation of the outcomes of action. As a result of these habitual and deliberative processes, drug use escalates so that people ultimately seek drugs compulsively (Redish et al. 2008).

INFERENCES ABOUT THE CAUSES OF HABIT PERFORMANCE

People often are aware of their habitual responses although they are largely unaware of the cuing mechanism that activates habits. Given this limited introspective access, people's explanations for their habitual responses are largely post hoc accounts. According to classic social psychology theories, when internal cues to action are weak, ambiguous, or uninterpretable, people infer what their motivations must be from observing their behavior and the context in which it occurs (Bem 1972).

The simple frequency of habit performance plausibly implies strong, consistent underlying motives. Such inferences could be correct in an historical sense, because people might accurately remember the goals that initially guided habit formation. However, they will not be correct concerning current habit performance. In support of such an inference, participants with stronger habits were more certain about their behavioral intentions and perceived the behavior as guided more by their goals than were participants with weaker habits, when in fact the opposite was true—intentions and goals were particularly poor predictors of strongly habitual behaviors (Ji & Wood 2007, Neal et al. 2012). People infer that goals underlie a range of habitual behaviors, even habits of compulsive drug seeking and use. Everitt & Robbins (2005) suggested that addicts' experience of wanting a drug is not a precursor of consumption but rather a post hoc rationalization of compulsive drug-use habits. Similarly, obsessive-compulsive disorders may originate in excessive habit formation, with irrational threat beliefs then inferred to explain the compulsively repeated behaviors (Gillan & Robbins 2014). Although people infer intentionality for a wide variety of automatically cued responses, when internal cues are strong and unambiguous, causal inferences

are unnecessary. Then, inconsistencies between habits and goals might just be labeled as such (e.g., "I can't help it, it's a habit").

The inference of motives behind habit performance is represented in some computational models as non-goal-mediated routine responding giving rise to goal representations. For example, in Sun et al.'s (2001) CLARION (Connectionist Learning with Adaptive Rule Induction Online) model, habitual responses that are controlled through bottom-up procedural knowledge can, over time, come to be represented in top-down rules via a rule extraction-refinement algorithm. In Cooper et al.'s (2014) goal circuit model, stimulus-driven habitual responses can activate goal representations that subsequently provide input to habits. In this way, active goals may be a consequence, rather than a precursor, of habitual action. From the perspective of RL models, this inference might occur through the model-based system adopting the values expressed in habit learning, perhaps to reduce computational overhead (Doll et al. 2012).

Goal inferences are sparked not only by the simple frequency of habit performance but also by the positive affect associated with many habits. Habits are likely to be favored due to the ease with which they can be performed compared with alternatives. Thus, consumers value using existing products and services over new ones because of the difficulty of learning new usage behaviors (e.g., computer program updates; Murray & Häubl 2007). Habits also are likely to be viewed positively due to the fluency or speed and ease of processing associated with frequently performed behaviors. High fluency is experienced as positive in part because it signals familiarity over uncertainty and success at processing and understanding, and this positive affect generalizes to evaluation of the activity (Reber et al. 2004). Habit inferences thus exploit a psychological calculus that favors what feels easy because it is well practiced over what feels more difficult because it is new. Being favorably disposed toward habits, people may infer that they intended to perform the response.

Although the inferences that follow habit performance may not be accurate descriptions of the mechanisms actually generating action, such inferences sometimes contribute to well-being. Repeated behaviors, such as students' choices of the same seat in a classroom, heighten feelings of comfort, confidence, and control despite that these choices might initially be random (Avni-Babad 2011). Furthermore, habit performance may promote coherence or comprehensibility of experiences and thus enhance meaning in life (S. Heintzelman and L. King, unpublished observation). However, inferences about habits are not always beneficial, and the transparency of habit knowledge to introspection can lead people to underestimate its usefulness. For example, when highly motivated to perform well, participants with good procedural knowledge at a task overrode their habits and responded thoughtfully, despite that this impaired task performance (L. Carden, W. Wood, D. Neal, and A. Pascoe, unpublished observation).

In summary, people may explain habit performance, even addictive habits, by inferring relevant goals and intentions. Despite being largely erroneous, the inference that habits were intended may seem intuitively plausible given response frequency. Also relevant, switching costs can discourage deviating from habits, and experienced fluency can increase liking for them.

CHANGING HABITS

Unwanted habits are at the root of many failed attempts at behavior change. Evidence comes from Webb & Sheeran's (2006) meta-analysis of 47 studies that successfully used persuasive appeals and other interventions to change participants' intentions. The changed intentions, however, only yielded change in behaviors that participants performed sporadically (e.g., course enrollment) and not in behaviors that could be repeated into habits (e.g., seat belt use). Even the largely effective implementation intentions, or if-then plans to act on intentions at particular times and places (Gollwitzer & Sheeran 2006), are not successful at controlling many strong habits (Webb et al. 2009).

From a habit perspective, difficulties in changing established behavior patterns do not reflect people's continuing desire to perform the old behavior or a failure of willpower. The central challenge is that old habits continue to be activated automatically by recurring environmental cues (J. Labrecque and W. Wood, unpublished observation; Walker et al. 2014). Even after new habits have been learned, old memory traces are not necessarily replaced (Bouton et al. 2011). Relapse can occur when old habit memories are activated by prior routines and other context cues.

Addressing the role of habit learning is a central challenge for the next generation of behavior change interventions (Marteau et al. 2012, Rothman et al. 2015). In response to this challenge, interventions can be designed to (*a*) impede the automated cueing of old, unwanted habits as well as (*b*) promote the repetition of a new, desired behavior into a habit.

Interventions to Impede Unwanted Habit Performance

To reduce interference from old habits, behavior change interventions can incorporate mechanisms of inhibition. In research investigating the spontaneous inhibition of unwanted habits in daily life, the most successful strategy involved thinking, "Don't do it," and being mindful of slip-ups (Quinn et al. 2010). This strategy also successfully controlled habit errors when participants were instructed to use it in an experimental task. As expected, it worked by enhancing cognitive control, not by decreasing habit strength (Quinn et al. 2010). Also effective is tying inhibitory plans to the cues that activate unwanted habits (e.g., "After dinner, I'll skip dessert as usual and substitute fruit"; Adriaanse et al. 2010).

Interference from old habits also can be reduced by changing cues in performance environments. Animal research suggests that habit performance is especially impaired when contexts shift, with goal-directed responding transferring more successfully across contexts (Thrailkill & Bouton 2015). One way to change habit cues is through managing exposure. For example, unhealthy eating habits can be curbed by increasing the salience or accessibility of healthy foods (Sobal & Wansink 2007). A study illustrated how people do this in daily life: At all-you-can-eat Chinese buffets, patrons with lower body mass index used chopsticks, chose small plates, put napkins on their laps, and sat with their sides or backs to the buffet (Wansink & Payne 2012). Another way that habit cues change is through naturally occurring life transitions, such as when people switch jobs or move house. Habit discontinuity interventions capitalize on this reduced exposure to cues that trigger old habits (Thøgersen 2012, Verplanken et al. 2008, Walker et al. 2014). Life transitions that alter habit cues can provide a window of opportunity to act on new intentions without competition from old habits (Wood et al. 2005).

Interventions to Promote Formation of Desired Habits

By encouraging the formation of new habits, behavior change interventions can be designed to habitize a new behavior so that it is maintained despite short-term desires and temptations. In an experiment illustrating how healthy habits can arm people against succumbing to food temptations (P.-Y. Lin, W. Wood, and J. Monterosso, unpublished data), participants learned in a computerized task to avoid chocolate (study 1) or to choose carrots (study 2). When later given options of eating unhealthy treats, participants continued to make habitual choices, at least when context cues automatically triggered the healthy habit. Also, echoing the factors that balance habits and goals, participants were most likely to act on their healthy habits when they lacked the willpower to deliberate about food choices.

Despite the promise of habit formation in maintaining desired behaviors, only a few interventions with nonclinical populations have built on the three pillars of habit formation–repetition in

stable contexts with appropriate reward schedules (see Lally & Gardner 2013, Rünger & Wood 2015). The importance of frequent responding was illustrated in Lally et al.'s (2010) field experiment in which repetitions of a simple health behavior (e.g., walking after dinner) required from 18 days to as many as 254 days in the same context to become habitual and performed without thinking. For exercise, Kaushal & Rhodes (2015) estimated that going to the gym became automatic within six weeks, assuming visits of four times per week. Unfortunately, few health or other behavioral interventions have adapted interval reward schedules to facilitate habit formation (Burns et al. 2012). However, the importance of stable cues was demonstrated in interventions using tooth brushing to cue dental flossing and form flossing habits (e.g., Judah et al. 2013, Orbell & Verplanken 2010). The few interventions built on the three components of habit formation have yielded promising results for weight loss (Carels et al. 2014, Lally et al. 2008) and consumption of healthy food in families (Gardner et al. 2014).

Interestingly, in a habit formation intervention, electronic reminders to perform a desired behavior increased repetition but also impeded automaticity and learning of context-response associations (Stawarz et al. 2015). Perhaps reminders engaged deliberate decision making that impaired learning context–response associations (see Associative and Reward Mechanisms in Habit Learning section). More passive reminders in the form of physical signs, although helpful in prompting initial repetition and habit formation, ultimately lost potency over time (Tobias 2009).

Additional evidence of the utility of habit formation comes from interventions that did not specifically target habits. For example, forming gym-going habits enabled new members of a health club to sustain working out (Armitage 2005), and forming nonsmoking habits enabled former smokers to remain abstinent a year after the end of a smoking cessation program (Baldwin et al. 2006). In a study of regular exercisers, approximately 90% had a location or time cue to exercise, and exercising was more automatic for those who exercised in a routine way and were cued by a particular location (Tappe et al. 2013).

Research on self-control also suggests the usefulness of habits for maintaining desired behaviors. People with high trait self-control do not appear to attain goals through inhibition of problematic desires but instead through forming habits that allow them to achieve goals without experiencing unwanted temptations (Galla & Duckworth 2015, Hofmann et al. 2012). Trait self-control generally fosters proficiency at performing tasks that require automation (de Ridder et al. 2012). Nonetheless, everyone tends to fall back on performing habits—both good and bad—when they lack the capacity or motivation to make decisions to act in nonhabitual ways (Neal et al. 2013).

In summary, through combating unwanted habits and ensuring that desired behaviors are repeated in ways that promote habit formation, interventions can promote adoption of behaviors that endure over time. These interventions adapt the habit strategies that people with effective self-control use in their daily lives to ensure successful goal attainment.

CONCLUSION

The current state of the science on habits has provided the definition that James (1890) requested, overturned behaviorists' conceptions of simple stimulus-response associations, and placed habits within broader models of goal-directed action. Habits reflect associative learning and the formation of context-response associations in procedural memory. Once habits form, perception of the context automatically brings the response to mind, and people often carry out that response. As habits strengthen, they gradually become independent of the incentive value of their consequences, and neural activation shifts from associative toward sensorimotor cortico-striatal brain regions. When repeated in a sequence, habitual responses also may be chunked together and activated as a unit. In short, our review provides a framework for understanding, predicting, and changing that

common component of everyday life in which behavioral control has been outsourced onto the context cues contiguous with past performance.

Although habits are largely insensitive to changes in goal structure and value, they interact in three different ways with deliberate goal pursuit. First, habits form in daily life as people pursue goals by repeating actions in particular performance contexts. Initially, goals and declarative task knowledge structure behavior. With repetition, responses and associated context cues are captured in procedural learning systems. Goals also may contribute to habit formation through heightening attention to certain stimuli and identifying the value of action outcomes. Given the profusion of direct and indirect connections between neural circuits underlying goal-directed and habitual (model-free) behaviors, goals can have a biasing influence on habit formation (Doll et al. 2012). Cross talk between habit systems and more deliberative action control, especially during habit formation, is consistent with an evolutionary history in which neural systems supporting more sophisticated planning capacities evolved on top of neural mechanisms associated with habits.

A second interface between goals and habits emerges after habits form. That is, habits provide an efficient baseline response that likely integrates with more effortful goal pursuit only when necessary, as when habits prove unreliable in a given context or when people are especially motivated and able to tailor responses to particular circumstances. Various factors impede people's ability to deliberate and thus tip the balance toward relying on habits, including time pressure, distraction, stress, and addiction. Addictive substances may in addition promote habit responding by accelerating habit learning.

A third way in which goals integrate with habits is through the explanations that people generate for their habits. Because habit automaticity is inaccessible to subjective experience, people must infer the reasons for such responses. A plausible inference for repeated behaviors is strong, consistent underlying motivations and goals.

The research we reviewed highlights a number of advantages to acting habitually. For example, habit knowledge is protected from short-term whims and occasional happenings, given that habits form through incremental experience and do not shift readily with changes in people's goals and plans. Also, by outsourcing action control to environmental cues, people have a ready response when distraction, time pressure, lowered willpower, and stress reduce the capacity to deliberate about action and tailor responses to current environments. Furthermore, habit systems are smart in the sense that they enable people to efficiently capitalize on environmental regularities.

As we noted at the end of the present review, understanding habits is important from the applied perspective of human health and welfare. Drug addictions and other compulsions appear to co-opt habit processes and reduce people's capacity to purposively guide their behavior. Lifestyle habits of poor diet and limited exercise are major contributors to chronic diseases. By building on an understanding of habit mechanisms, addiction treatments as well as interventions to change lifestyle behaviors may successfully disrupt these unwanted habits and help people to form more effective habits that meet their goals for healthy, productive lives.

DISCLOSURE STATEMENT

ACKNOWLEDGMENTS

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