

Rationalizing Constraints on the Capacity for Cognitive Control

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Abstract

Humans are remarkably limited in (a) how many control-dependent tasks they can execute simultaneously, and (b) how intensely they can focus on a single task. These limitations are universal assumptions of most theories of cognition. Yet, a rationale for *why* humans are subject to these constraints remains elusive. This review draws on recent insights from psychology, neuroscience and machine learning, to suggest that constraints on cognitive control may result from a rational adaptation to fundamental computational dilemmas in neural architectures. The reviewed literature implies that limitations in multitasking may result from a tradeoff between learning efficacy and processing efficiency, and that limitations in the intensity of commitment to a single task may reflect a tradeoff between cognitive stability and flexibility.

Keywords: information processing limitations; multitasking; task switching; visual attention; working memory

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Highlights

- To explain human behavior, most general theories of cognition assume rather than explain limitations in (a) the number of control-dependent tasks that can be performed simultaneously (i.e., multitasked) and (b) the amount of cognitive control that can be allocated to a single task.
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 - Limitations in the capability to multitask can be explained by representation sharing between tasks. Computational modeling suggests that neural systems trade the benefits of shared representation for rapid learning and generalization—a mechanism increasingly exploited in machine learning—
10 against constraints on multitasking performance.
 - Experimental studies posit a tradeoff between cognitive stability and cognitive flexibility. Computational analyses of this tradeoff suggest that adaptations to high demands for flexibility limit the amount of control
15 that can be allocated to a single task.
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Glossary

Cognitive Flexibility: The ability to quickly adapt information processing to
20 changing task demands.

Cognitive Stability: The ability to successfully pursue a task in the face of
distraction.

25 **Dual-Task Interference:** Decrements in task performance when an attempt
is made to execute a task at the same time as another task, relative to when it
is performed alone.

Multitasking: The *simultaneous* execution of two or more tasks. We distin-
30 guish this use of the term from broader uses, such as the switching between
multiple tasks [1].

Resource: A cognitive commodity (e.g., a set of representations) that are re-
quired to execute a task. It is often assumed that resources are limited in some
35 way (e.g., that only one or a restricted subset of representations of a given type
can be active at a single time).

Task: A consistent mapping from the features of a stimulus along a given di-
mension (e.g. the color of a word) to a set of actions along a given response
40 dimension (e.g. verbal responses).

Task Representation: The full representation of all information (e.g., per-
ceptual, contextual and response) needed to execute a particular task.

45 1. The Role of Capacity Constraints in Human Cognition

One of the most remarkable features of human cognition is the ability to rapidly adapt behavior in a changing world. This is often attributed to the capacity for *cognitive control*—the ability to flexibly direct behavior in pursuit of a goal. Cognitive control is engaged by all of the higher mental faculties that distinguish humans from other species, including reasoning, problem solving, 50 planning, and the use of symbolic language [2]. Yet, humans are strikingly limited in how many control-demanding **tasks** (see Glossary) they can perform at the same time (e.g., reading a document while listening to a friend) or how intensely they can focus on a single task (e.g. parsing a mathematical equation in a noisy environment). The significance of these limitations is not only apparent 55 in daily life. They are also a fundamental premise of most general theories of human cognition (e.g. [3, 4, 5, 6, 7, 8]). These theories posit that the exertion of cognitive control is associated with a cost, and that humans consider this cost when making decisions about how to allocate control [8, 9, 10]. The notion of a 60 cost, and concomitant constraints on control, can help integrate a wide range of empirical findings concerning the allocation of control [11, 12, 13, 14], the selection between cognitive heuristics [6], planning [15, 16] or cognitive impairments in depression [17]. Yet, none of these theories provides an explanation for *why* control-dependent processing would be subject to these limitations in the first 65 place.

Here, we review two fundamental, computational dilemmas that arise in neural systems, and suggest that these provide a rational account of constraints on cognitive control. First, we review empirical and computational evidence suggesting a tradeoff between the rapid acquisition of novel tasks (learning efficacy), 70 that is promoted by sharing **representations** across tasks, on the one hand; and **multitasking** capability (processing efficiency) that is achieved by separating representations and dedicating them to individual tasks, on the other hand. The work reviewed suggests that the brain’s limitations in the ability to simultaneously execute multiple control-demanding tasks may reflect a preference to

75 learn tasks more quickly, and generalize that learning to other tasks: Immediate
rewards associated with quickly acquiring a task may often outweigh greater but
later rewards associated with the ability to execute that task in parallel with
others. On this view, a *purpose* of cognitive control is to prevent the simulta-
neous execution of tasks that share representations, to avoid the potential for
80 interference that could arise if those tasks required conflicting representations
to be active at the same time. It is thus the sharing of representations that
makes tasks control-dependent, forcing people to allocate control to only one
such task at a time, and requiring them to flexibly switch between tasks in
order to achieve more than one. This need to switch between tasks gives rise
85 to a second dilemma, the tradeoff between **cognitive stability** and **cognitive**
flexibility: Greater allocation of control to one task (e.g. parsing a mathemat-
ical equation) results in greater activation of the neural representations needed
to perform that task; but, due to persistence of this neural activity, this makes
it more difficult to switch to another task (e.g. responding to a phone call)
90 [18, 19, 20]. In the second part of this article, we review evidence for the hy-
pothesis that constraints on the amount of control allocated to a single task
result from a bias in this tradeoff, toward the ability to flexibly switch between
tasks. Finally, we discuss how the two dilemmas may account for limitations in
other domains of human cognition, such as constraints on working memory and
95 visual attention, as well as cognitive impairments associated with psychiatric
disorders.

2. Constraints on Multitasking Capacity

One of the key characteristics of cognitive control is a limitation in the num-
ber of control-demanding tasks that humans can execute at the same time. This
100 constraint is intuitively obvious (e.g., the inability to carry out a mathemati-
cal calculation while planning a grocery list). This has been defined as a core
characteristic from the earliest theories of cognitive control [21, 22], and used to
distinguish control-dependent processes from automatic processes: the former

are assumed to rely on control for execution, and therefore must be performed
 105 in serial (i.e., one at a time); whereas the latter do not rely on control and can
 operate in parallel (i.e., be multitasked). The distinction between serial versus
 parallel execution is literally paradigmatic. **Dual-task interference** is uni-
 versally used to operationalize (experimentally “diagnose”) control-demanding
 processes in the laboratory: a task is considered to be control-dependent if
 110 it cannot be executed in parallel with another control-dependent task without
 interference [21, 22, 23]. Thus, understanding the constraints associated with
 cognitive control amounts to understanding the inability to execute control-
 demanding tasks in parallel, and requires identifying the cause of dual-task
 interference.

115 The most common explanation for the processing constraints associated with
 control is that these reflect a limitation intrinsic to the mechanisms responsible
 for control itself (e.g., reliance on a single, centralized and capacity-limited con-
 trol mechanism [21, 22, 24, 25, 26], akin to the central processing unit (CPU, or
 core) of a traditional computer. However, this analogy is problematic, given the
 120 enormous capacity that the brain holds for parallel processing in other domains
 (e.g. the simultaneous integration of hundreds of visual features into an object,
 or simply walking and talking at the same time). This analogy also seems out-
 dated, since even the most basic of computers now almost always use more than
 one core. Alternative accounts have been offered in the past, including ones
 125 that align more closely with the idea that control reflects a response to—rather
 than the source of—constraints imposed on processing. In the section that fol-
 lows, we review primary theories concerning constraints on human multitasking
 performance and their relationship to cognitive control.

2.1. The Costs of Shared Representation for Multitasking Performance

130 Historically, there have been three broad classes of theories that address
 the limitations in human multitasking ability and their relationship to cognitive
 control (see Table 1 for an alternative classification of theories based on their
 assumptions about resources). All of them assume that these limitations reflect

some form of shared resource(s), but differ in where this occurs and the capacity for sharing. The first class, “structural bottleneck theories”, assume the
135 existence of a central resource that is required for processing of all tasks¹, and further assume that this resource can be used for only *one* task at a time (Fig. 1A). Structural bottleneck theories differ in where they locate this central resource, ranging from perceptual processing [27] to response selection [26, 28, 29]
140 or response initiation [28, 30, 31].

The second class of theories, “unitary resource theories”, share the assumption of a central, limited resource. However, they posit that the central resource (sometimes labeled “attention” [25]) can be divided between tasks (Fig. 1B). Thus, unitary resource theories assume that tasks can be executed in parallel,
145 with the caveat that the unitary resource must be divided between them, leading to a trade off in performance between tasks [25, 32, 33]. In this sense, they represent a graded version of structural bottleneck theories.

Finally, “multiple resource theories” renounce the idea of a single, centralized, limiting resource. Instead, they presume a multitude of independent, specialized (“local”) resources (see Box 1 for how resources can be defined).
150 A task may demand one or more of such resources in various combinations. Some propose that each local resource can only be used by one task at a time [34, 35, 36, 37] (Fig. 1C) whereas others propose that some resources can be shared between tasks (Fig. 1D), similar in concept to a unitary resource but
155 without assuming that such resources are required by all tasks [38, 39]. Multiple-resource theories became increasingly successful in explaining multitasking phenomena in laboratory tasks [37, 38, 40, 41] and in real-world scenarios [42, 43]. In addition, these theories are supported by recent numerical and analytical work, suggesting that even modest amounts of resource sharing between tasks
160 can be sufficient to drastically limit the multitasking capacity of a neural system [44, 45, 46], and that this effect scales with the number of processing steps (lay-

¹The central processing bottleneck is often considered to be “amodal” insofar as it is required by all tasks, irrespective of their modalities (sensory, motor or otherwise).

ers) in the network [47]. However, despite growing empirical and quantitative support, multiple-resource theories still lack a principled explanation for why a neural system, such as the human brain, would rely on shared resources between tasks at all, given the constraints on processing that this imposes.

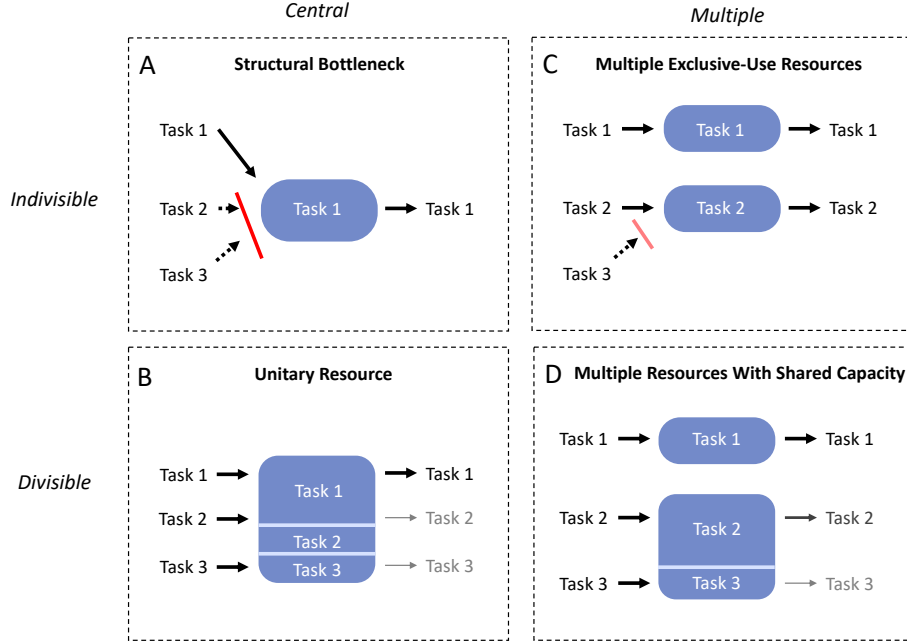


Figure 1: **Classification of Resources in Theories of Human Multitasking.** Theories differ according to whether they assume that tasks require the same, central resource or local task-specific resources (central vs. multiple), and the way in which those resources can be allocated (indivisible or divisible). (A) *Structural bottleneck*. A central resource constitutes a bottleneck in that it is required for execution of all tasks, and can operate only one of those at a time; if the resource is engaged by one task, it causes a delay in the processing of others. (B) *Unitary resource*. Tasks rely on a unitary centralized resource, but it can be allocated to multiple tasks at the same time; task interference occurs if the demands of those tasks exceed the available capacity of the unitary resource. (C) *Multiple exclusive-use resources*. Tasks rely on local, task-specific resources, each of which can only be used for one task at a time; interference arises if two tasks make simultaneous use of the same resource. (D) *Multiple resources with shared capacity*. Local, task-specific resources can be shared; interference arises if the capacity of a local resource is exceeded by the number of tasks using it at the same time.

All three categories of theory outlined above ground their assumptions about resource sharing in empirical evidence: If the simultaneous execution of two tasks leads to dual-task interference then they are likely to share a common resource (whether central or local) [39]. However, to avoid circularity, one needs
170 more than behavioral criteria when deciding about the number and types of resources [48]. This theoretical issue is exaggerated in theories that propose multiple resources, as highlighted by Meyer & Kieras (1997, p. 11): *“One [...] [concern] is that the concept of multiple resources lacks sufficient principled constraints. In the absence of such constraints, there is a temptation to hypothesize*
175 *new sets of resources whenever additional problematic data are collected. This could lead ultimately to an amorphous potpourri of theoretical concepts without parsimony or predictive power”*. In neural architectures, two tasks can be described as sharing a resource if they rely on the same set of representations for processing (see Box 1). From this perspective, explaining multitasking limita-
180 tions requires specifying *when* and *why* representations might be shared between tasks. Computational investigations in the domains of semantic cognition and task acquisition, as well as machine learning, have begun to provide insights into this, most of which identify benefits of representation sharing for learning and generalization.

Article	Number and Types of Resources				Divisibility of Resources	
	Central			Task-Specific	Yes	No
	Perception	Response Selection	Response Initiation			
Verbal Theories						
Welford (1952) [49]	×					×
Broadbent (1957) [27]	×					×
Smith (1967) [50]		×				×
Allport, Antonis & Reynolds [34]				×		×
Kahneman (1973) [25]	×			×	×	
Keele (1973) [30]			×			×
Kinsbourne & Hicks (1977) [51]	○			×		×
Shiffrin & Schneider (1977) [22]	×					×
Navon & Gopher (1979) [38]				×	×	
Navon & Miller (1987) [52]				×	×	
Wickens (1991) [39]	○			×	×	
DeJong (1993) [28]		×	×			×
Pashler (1994) [26]		×				×
Mathematical Models						
Logan & Gordon (2001) [53]				×	×	
Townsend & Wenger (2004) [28]				×	×	
Computational Models Based on Symbolic Architectures						
Meyer & Kieras (1997) [36]				×	×	×
Byrne & Anderson (2001) [35]	×			×		×
Salvucci & Taatgen (2008) [37]	×			×		×
Computational Models Based on Connectionist Architectures						
Feng et al. (2014) [44]	○			×	×	
Musslick et al. (2016, 2020) [45, 54]	○			×	×	

Table 1: **Classification of multitasking theories based on their assumptions about resources.** In contrast to task-specific resources, central resources are required to operate every task, and can be distinguished by the stage of processing they reside. Resources can either operate one task (not divisible) or multiple tasks (divisible) at the same time. Crosses indicate assumptions that are stated in the respective article. Circles indicate cases where an assumption is not explicitly stated but is either (1) acknowledged as a possibility or (2) can be derived from other assumptions of the model/theory. Theories are grouped by whether they are expressed in verbal or quantitative form (cf. Box 1 for a comparison of symbolic and connectionist architectures). Note that the present list of articles is by no means complete and represents only a subset of the literature.

185 *2.2. The Benefits of Shared Representations for Learning*

The sharing of representations between tasks is evident in many domains of cognition, ranging from visual processing [55, 56] and numerical judgement [57] to language acquisition [58], semantics [59] and social cognition [60]. Yet, little is known about when and why people acquire shared representations across tasks.
190 That is, what are the conditions under which neural systems develop shared representations in the context of task performance, and what are their benefits for behavior? Answers to these questions arise from the study of category learning in semantic cognition, and are exploited in the form of machine learning paradigms for the acquisition of multiple related tasks.

195 Early computational studies of category learning suggested that neural systems are likely to learn shared representations between semantic categories if they are statistically related [61, 62]. Saxe, McClelland & Ganguli (2019) [63] formalize this idea in a mathematical theory of semantic cognition, and show that neural networks are biased toward learning shared representations between
200 two categories (e.g. trees and plants) if the set of features defining each of the categories overlap (e.g. trees and plants have in common that they grow but are not motile). A similar observation can be made for the acquisition of tasks: neural networks are more likely to acquire shared representations between cognitive tasks if they overlap in terms of task-relevant stimulus features (e.g. the
205 same set of visual features relevant for task performance) [54, 64, 65]. The findings of Saxe et al. and others [59, 66, 67] also suggest that shared representations are not just a “byproduct” of learning; they allow networks to learn more rapidly and generalize better. That is, they increase the efficacy of learning. For instance, network architectures that promote the learning of shared
210 semantic representations across sensory modalities facilitate the acquisition of novel semantic concepts [66]. Similarly, architectural biases toward the learning of shared representation between tasks can accelerate the sequential acquisition of these tasks [65, 68].

Machine learning applications have also demonstrated and begun to exploit
215 the benefits of shared representations for learning. In that field, “multi-task

learning” (as distinct from “multitasking”) refers to settings in which an agent is trained on a set of auxiliary tasks that share representations with the task to be learned, exploiting the fact that similarities among those tasks can lead to shared representations that can help improve generalization and thereby acquisition
220 of the target task [69, 70, 71]. This has produced significant improvements in computer vision [72, 73], natural language processing [74, 75] and speech recognition [76].

These converging lines of work all indicate that sharing of representations can improve the efficacy of learning (i.e., generalization and speed of acquisition).
225 However, as noted in the previous section, this introduces the potential for interference in multitasking, and a concomitant reliance on control to serialize task execution, and thus may come at the cost of efficiency of processing [65]. In the next section, we discuss how this tradeoff can help rationalize constraints associated with cognitive control and other closely related functions such as
230 visual attention and working memory.

2.3. Trading the Costs and Benefits of Shared Representations

The tradeoff between learning efficacy and processing efficiency suggests that the benefits and costs of control-dependent processing may be computationally intertwined (Fig. 2), and reflect the factors described above. The benefits of
235 cognitive control are that it allows novel tasks to be acquired rapidly by exploiting the advantages of shared representations while minimizing the risk of conflict that this introduces [22, 77, 78]. For instance, participants can quickly learn to map familiar stimuli onto new responses [71, 79] (e.g. learning how to indicate a color word with a button press). Biologically inspired models of cog-
240 nitive control suggest that the brain may achieve this by recombining existing representations for task-relevant stimuli and responses [54, 64, 78, 80]. This suggests that novel tasks may rely, at least initially, on representations shared with other tasks, and thus may be subject to interference from those tasks (Fig. 2C). However, this can be mitigated by the engagement of control, by limiting the
245 engagement of representations shared by multiple tasks to one task at a time

[80, 81]. From this perspective, constraints on multitasking capability reflect the engagement of control as a rational adaption to resource limitations, rather than an intrinsic limit in control mechanisms themselves [45, 54]. Furthermore, these constraints can be considered a *cost* incurred in exchange for the benefits gained from shared representations: the repurposing of existing representations for new tasks allow these to be acquired rapidly, but at the cost of constraints on multitasking capability and dependence on control [54, 82]. This hypothesis is supported by a mathematical analysis of this relationship in linear networks [65, 54], as well as artificial agents that optimize the tradeoff between learning efficacy and multitasking capability [68, 83]. The latter work suggests that it can be optimal, under finite time horizons, for neural agents to harvest immediate rewards from tasks that are learned quickly, at the cost of having to execute them in serial. However, once acquired, repeated multitasking practice can lead to a separation of representations between tasks [84] (see Box 1). The separation of representations between tasks may be a crucial ingredient of automaticity in that it frees tasks from interference, thereby reducing their reliance on control (cf. Fig. 2D) [45, 54]. The tradeoff between shared versus separated representations may also inform constraints in cognitive functions related to cognitive control, such as working memory and visual attention.

2.3.1. Working Memory

The costs and benefits of shared representation may apply at all levels of representation, including ones that guide the selection of task-relevant modules over an extended period of time (see Box 2). This embraces representations that are held in short-term buffers, such as contextual information, or “task goals” in working memory. Such abstract representations that influence processing at a broader level (e.g, at the “task selection” level) are traditionally considered to support control-dependent processing [3, 85]. The principle introduced above, that multitasking interference arises if two or more tasks require engagement of different representations within the same module (cf. Box 1), may equally apply to such representations. Indeed, the limited capacity of short-term buffers, such

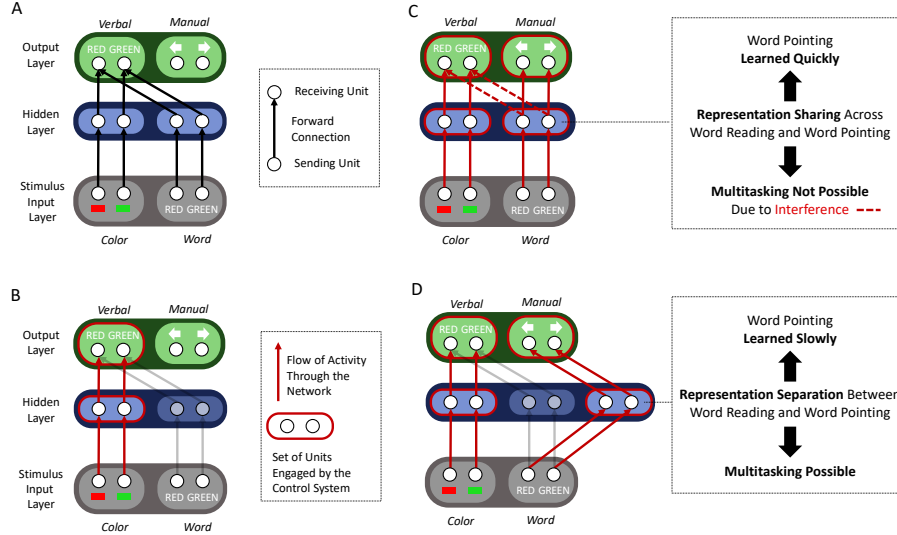


Figure 2: Tradeoff Between Learning Efficacy and Processing Efficiency in a Neural Network. Tasks are implemented as mappings between stimulus features (units in the input layer) and responses (units in the output layer), through an internal representation of stimulus features (units in the hidden layer). (A) The network implements two tasks: mapping colors to verbal responses (color naming) and mapping words to verbal responses (word reading). All units are assumed to be inhibited at rest, preventing flow of activity through the network. (B) To execute color naming, the control mechanism (not shown) engages representations for colors and verbal responses in the hidden and output layers, respectively. This prevents interference from the word reading task. (C-D) The network may learn a new task—indicate the word with a manual response (word pointing)—by mapping the existing representations for words to manual responses (C) or, alternatively, by learning new representations dedicated to mapping from words to manual responses (D). The former requires less time to learn but results in a shared representation between word reading and word pointing and thus dependence on control; when prompted to multitask color naming with word pointing, the control mechanism must engage representations for colors and words in the hidden layer, as well as verbal and manual responses in the output layer. In (C), this results in an implicit engagement of the word reading task because word reading and word pointing share a representation, leading to interference with color naming. Separated representations in (D) prevent such interference, but take longer to learn. Human behavior is consistent with (C), suggesting that humans are biased toward representation sharing [54].

as working memory, is often attributed to interference between the representations they maintain [86, 87, 88] (for a review, see [89]).

The role of shared representation for the active maintenance of information is nicely illustrated by a recent network model of visual working memory by Bouchacourt & Bushman (2019) [86]. That model consists of two layers: (1) a “sensory network” which is composed of independent sub-networks, each dedicated to represent a visual stimulus, and (2) a “random network” which is randomly and reciprocally connected to the sensory network. Representations for visual stimuli in the sensory network lead to corresponding activations in the random network which then engage, through feed-back connections, the same representations in the sensory network. This reciprocal connectivity ensures that representations for visual stimuli are maintained, despite removal of external input (the visual stimulus) to the sensory network. The random connectivity provides the network with the flexibility to store any arbitrary item. However, the downside of this random connectivity are shared representations in the random network between stimuli from different sensory sub-networks. Once two visual stimuli share a representation in the random network they may interfere with one another, limiting working memory capacity. Thus, from this perspective, the working memory mechanism can be viewed as an extreme example of a set of representations shared by *any* task that requires sustained activity of a visual stimulus, and is in this respect subject to the same limitations—for the same reasons—as any other control-dependent process.

2.3.2. Visual attention and the “binding problem”

An important consequence of shared representations in visual processing modules is the “binding problem”, that has been closely linked to the role of attention. The binding problem concerns the assignment of stimulus features to individual objects [90], and arises if different objects are represented by the same (shared) set of feature representations. For example, in a display containing a red car and gray house, if the two objects engage the same set of color representations (i.e., use the same population of neurons to represent color),

then it may be impossible to determine which one activated red and which one gray. That is, the sharing of representations of features—sometimes referred to as “compositional coding” [91]—poses the risk of confusion if more than one object must be identified at the same time [48]. This is exactly analogous to the problem posed by sharing the representations required to perform tasks [92]. Fig. 2 shows two ways in which the system can deal with this problem in the task domain: If tasks share representations then, as discussed above, control must be used to limit processing to only one of them at a time (Fig. 2C). However, the system may also, at the expense of additional learning, commit separated, task-dedicated representations to the mappings from the stimuli to the responses for each task (Fig. 2D).

These two solutions correspond directly to ones that have been proposed to solve the binding problem in the visual system: use composition coding [91], and limit processing by allocating attention to only one object at a time so that only the features associated with that object are active in the set of representations for a given dimension [48, 92]; or dedicate separate representations to the combinations of features for each object (“conjunctive coding” [93, 94]), thus binding those features directly to the object. The latter is observed for highly familiar objects with combinations of features [95] (e.g. line segments that make up letters, or the features of familiar animals such as the color and stripes of a tiger or the size and trunk of an elephant).

There is strong evidence that, despite the risk of interference, the visual system also makes use of compositional coding (i.e., shared representations) of features such as colors and locations [96, 97, 98]). For example, it is assumed that this supports spatial invariance (e.g. the ability to detect the color of an object with the same population of neurons, irrespective of its location). As noted above, this approach has been used in machine learning to improve efficacy of learning, e.g. to achieve object recognition [99, 100]. Findings from classic studies of visual attention also provide strong support for the use of compositional coding, evidenced by the binding problem that it poses, and the serialization of processing used as a solution [48]. In such studies, participants

must detect an object composed of an arbitrary combination of features (e.g., a red T) in a field of distractor objects that combine the same features in other ways (e.g., green T's and red L's). Errors in such tasks often involve confusion
340 over the assignment of features to objects; and response times typically scale linearly with the number of distractors, which is taken as evidence of serial allocation of visual attention to each object individually. These observations inspired “feature integration theory”, which proposed that the purpose of attention is to integrate percepts by serially binding objects and their features
345 [48], though the mechanism for this process was not specified.

A variant, or perhaps elaboration, of this view is that binding is not implemented directly by attentional mechanisms, but rather by the connections of the network that link objects with compositional representations of their features (i.e., ones that are shared across objects); and that the role of attention is simply to insure that only one object is represented at a given time, to prevent the
350 confusions that would arise if the features of different objects were represented at the same time over the same set of representations. This directly parallels the role of control in averting conflict among tasks that share representations, and the constraints in the number of representations that can be actively maintained
355 in working memory. The appeal of this view is that it provides a unified explanation of the conditions under which the constraints of seriality arise, and why these are associated with the engagement of control—whether to select what to attend visually, represent in working memory, or task to perform—all in terms of a common set of fundamental principles of representation and processing in
360 neural systems that apply across domains. All reflect a tradeoff that favors the advantages of shared (i.e., compositional) representations—whether for efficacy of learning, flexibility of processing, and/or efficiency of representation—at the expense of the efficiency of execution afforded by the ability to process separated (e.g., conjunctive) representations in parallel.

365 3. Constraints on Control Allocated to a Single Task

Theories of cognitive control imply that higher amounts of control allocated to a single task lead to higher cognitive stability [8, 12, 13, 14, 80]. Yet, there appears to be a limitation in *how much* control can be allocated [9]. This constraint seems puzzling from a rational perspective: Why would a system refrain
370 from allocating maximal control to a task to which it is already committed? One possible explanation is that there are also opportunity costs associated with the dynamics of allocating control: the greater the allocation of control to one task, the harder it is to switch to others. Such dynamics can arise from competitive interactions between representations required to allocate control in
375 just the way they do for any other set of representations (see Box 2), and may help explain the stability-flexibility dilemma that has been described for control, and constraints observed on the intensity of its allocation.

3.1. The Stability-Flexibility Dilemma

Successful goal-directed action requires balancing antagonistic demands: On
380 the one hand, we need to maintain and shield task goals in the face of distraction (cognitive stability); on the other hand, quick and flexible reconfiguration is often required to perform a different task when the environment changes (cognitive flexibility) [18, 19, 20]. Cognitive stability can be quantified in the laboratory, by instructing participants to perform a single task in the presence
385 of distractors, and by measuring how much the distractors affect participants' performance (see Box 3). Cognitive flexibility can be assessed by measuring how fast participants can switch from one task to another. Critically, there appears to be a tradeoff between the two quantities across participants: On the one hand, individuals with greater flexibility tend to be more distracted by task-irrelevant
390 information [101, 102, 103]; on the other hand, individuals with high resistance to distraction, such as patients with Parkinson's disease, tend to be cognitively inflexible [104, 105]. In addition, reward and positive affect can bias individuals toward greater flexibility, at the expense of cognitive stability [106, 107, 108]. A

growing body of work suggests that the neurotransmitter dopamine may play a
395 role in regulating this balance (for a comprehensive review, see [109]).

3.2. *Optimizing the Balance Between Cognitive Stability and Flexibility*

Computational analyses of the tradeoff between cognitive stability and flexibility suggest that constraints on control may help optimize this tradeoff. A number of biophysically inspired models of task control [88, 110, 111, 112] rely
400 on the assumptions that (a) representations for different tasks compete with one another (due to representation sharing), and that (b) the representation of a task can persist in time, slowing representational reconfiguration for a subsequent task (see Box 2). These models describe competing task configurations as different energy landscapes (Fig. 3A-B). In these landscapes, the information
405 that specifies which task to perform (such as task instructions, relevant feature dimensions, and any other context information relevant to control) is assumed to be represented as stable patterns of neural activity that correspond to states with low energy, located at the bottom of an energy well in the landscape (an “attractor”). When such task information is presented to the network, its pattern of activity evolves such that the system moves to that attractor (analogous
410 to a ball rolling along a surface to the bottom of the nearest well). If the representation of the task information corresponds to a deep attractor, then even with small perturbations (e.g. due to noise) the system is most likely to settle back to the same state (akin to a ball bouncing around in a deep well). Thus,
415 deep attractors make the system robust to noise. Conversely, shallow attractors make the system more susceptible to noise (i.e., make it easier for the ball to pop out of the well), but also make it easier to switch from one state to another.

By considering the representations responsible for control as attractors, Muslick et al. (2018) [111] show that constraints on control allocation (restricting
420 the depth of attractors) can promote flexible task switching but this comes at the expense of robustness to distractors (Fig. 3C).² Their simulations suggest that

²An alternative solution this problem may be the flexible “gating” of task-relevant infor-

higher constraints on control allocation (shallower attractors) are optimal in environments with higher demand for (e.g., greater frequency of) task switches (Fig. 3D). By fitting the model to individuals’ behavior in a task switching paradigm, Musslick et al. (2019) [112] further demonstrate that the behavior of participants in environments with a high rate of task switches can be best explained with higher constraints on control, compared to participants in environments with a low rate of task switches. This is in line with a growing number of studies showing that participants shift their balance to favor cognitive flexibility over stability if task switches become more likely [116, 117, 118, 119, 120, 121]. Together, these computational and empirical results suggest that it can be useful to limit the amount of control allocated to a single task, given that this facilitates flexible switching between tasks.

4. Concluding Remarks and Future Directions

Constraints on our capacity for cognitive control pervade all forms of human cognition that involve control-dependent processes, ranging from lower-level processes such as perception, memory retrieval, and action selection, to higher level ones such as reasoning, problem solving, planning and language. Here, we considered constraints on (a) the number of control-demanding tasks that humans can execute simultaneously, as well as (b) the amount of control that they can allocate to a single task, and reviewed recent work that suggests *why* the allocation of control might be subject to these constraints in the first place, in terms of a common set of principles concerning the representation and processing of information in neural network architectures (see Boxes 1 and 2). The literature reviewed suggests two fundamental computational dilemmas that arise from

mation into the system, by switching from deep to shallow attractors once a task switch is required [113, 114]. However, this approach seems less parsimonious in that it requires additional mechanisms to optimize the energy landscape of the system. Moreover, even with a gating mechanism, task representations would require time to be reconfigured, resulting in switch costs [115].

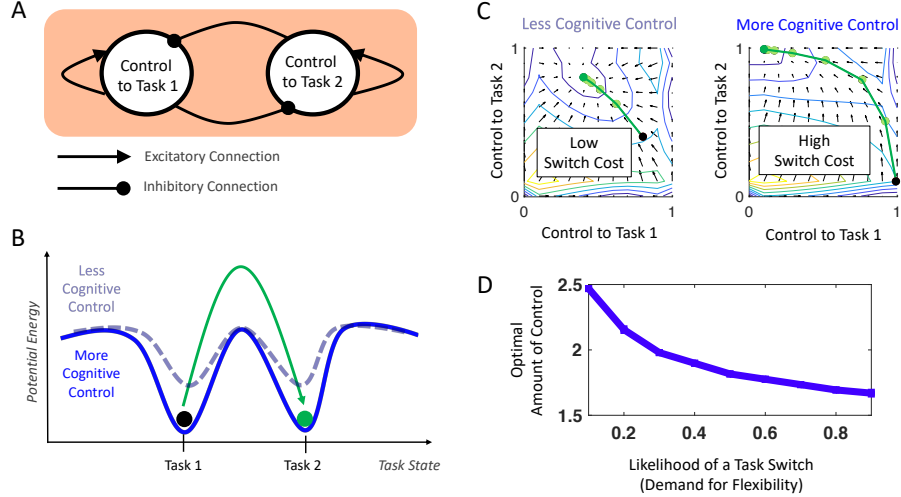


Figure 3: **Modeling the Stability-Flexibility Tradeoff.** (A) Two-unit network used to simulate the stability-flexibility tradeoff [110, 111, 112]. Each unit represents a control signal for one of two tasks. The activity of each unit corresponds to the amount of control allocated to the corresponding task, that is determined by a recurrent excitatory input from itself and an inhibitory input from the other unit, as well as external input such as a task cue (not shown). (B) The network implements a dynamical system whose state of activity (x-axis) is determined by its energy (y-axis; cf. [18, 110, 111, 122]). The system has two stable states (attractors), one for executing each of the two tasks. The network’s parameters determine the depth of the attractors. Deep and shallow attractors correspond to networks with high and low amounts of control allocated to each task, respectively. Thus, deep attractors implement cognitive stability, whereas shallow attractors implement greater flexibility, making it easier to switch from one state to another (green arrow). (C) Simulated activation trajectories [111] for shallow (left) and deep (right) attractors are shown as a series of connected light green dots, evolving from the control attractor for Task 1 (black) to the control attractor for Task 2 (green). Contour lines and arrows indicate the energy and shape of the attractor landscape after a task switch from Task 1 to Task 2. With more control allocated to Task 1, the network requires more time steps to switch to Task 2. (D) Simulations show that the optimal amount of control allocated to a task decreases with the frequency of task switches [111].

these principles. The first is reflected in recent insights from studies of semantic cognition and task acquisition in both cognitive science and machine learning, which suggest a tradeoff between learning efficacy and processing efficiency. The former is promoted by the sharing of representations across tasks, whereas

450 the latter is achieved by separating representations between tasks thereby per-
 mitting parallel processing (i.e., multitasking). Findings concerning working
 memory and visual attention suggest a similar tradeoff between the represen-
 tational efficiency of compositional coding using shared representations but at
 the expense of serial processing, and the efficiency of conjunctive coding that
 455 affords parallel processing but at the expense of dedicating separate represen-
 tation to each item that must be represented. From this perspective, capacity
 constraints and the requirement for serial processing arise not from limitations
 intrinsic to the mechanisms responsible for control, but rather from the use of
 shared representations—whether for features of visual objects, information ac-
 460 tively maintained in working memory, or the mappings required to perform a
 task—that demand the allocation of control in order to avoid interference or
 confusion that would arise from their use for different purposes at the same
 time. Furthermore, the competitive dynamics within a set of shared representa-
 tions in a network can simultaneously account for the tradeoff between cognitive
 465 stability and flexibility, and constraints in the intensity of control allocated to
 any single task that arise because of this.

An understanding of the fundamental computational dilemmas faced by the
 representation and processing of information in neural architectures may also
 provide a novel perspective on cognitive function in psychiatric disorders, many
 470 of which involve deficits in control-dependent behavior [123]. One example
 concerns the role of dopamine function in the stability-flexibility tradeoff [109]:
 enhanced resistance to distraction observed in patients with Parkinson’s disease
 [124, 125] may reflect an imbalance toward cognitive stability at the expense
 of behavioral rigidity and inflexibility [104, 105]. Another example concerns
 475 processing and inference in patients with Autism Spectrum Disorder (ASD).
 On the one hand, patients with ASD exhibit a variety of cognitive deficits,
 e.g. in abstracting and synthesizing information across experiences [126, 127].
 On the other hand, patients with ASD outperform healthy controls in visual
 search tasks that require one to identify a particular combination of features
 480 among distractors (“conjunctive search”, e.g. finding a green circle amidst red

circles and green squares) [128, 129, 130]. As discussed above, the processing of multiple visual stimuli can lead to interference if representations of features are shared across objects (i.e., compositional coding), rather than assigning each combination of features a separate representation (i.e., conjunctive coding). It
485 has been hypothesized that patients with ASD exhibit relatively greater reliance on separated than shared representations for features [131]. While this would afford greater parallelism (and thereby efficiency) in visual search, it should come at the cost of flexibility and generalization as is observed in such patients.

This review has focused on two tradeoffs—learning efficacy versus processing
490 efficiency, and stability versus flexibility—however there are of course others faced by cognitive systems [132, 19, 133]. For example, another one concerns the decision between selecting actions that yield known rewards (exploitation) and ones with unknown rewards but that may yield new information that leads to greater rewards in the future (exploration) [134]. It has been hypothesized
495 that boredom may reflect an adaptive signal meant to manage the explore-exploit dilemma, by leading agents to explore new options when current ones are highly predictable [135, 136, 137]. A promising avenue for future research is to explore how other limitations on human cognition, such as the inability to exert control over extended periods of time, may result from such tradeoffs (see
500 Outstanding Questions).

Constraints of cognitive control remain a crucial building block for general theories of cognition. Thus, an improved understanding of these constraints may help understand their consequences in other domains of cognition. The study of computational dilemmas, as reviewed here, presents a novel approach to this
505 matter, and may help rationalize these constraints in neural systems and relate them to the broad inventory of phenomena associated with cognitive function.

Box 1: Resource Sharing in Symbolic Architectures and Connectionist Models

510 The terms “shared resource” and “shared representation” describe similar concepts in different models of human multitasking. Models based on symbolic architectures [35, 36, 37], such as ACT-R [3] and EPIC [36, 40] consist of different components. For example, in ACT-R, there are components for representing declarative information (e.g., sensory information or more abstract semantic
515 knowledge), as well as procedural modules for the manipulation of information (e.g., productions for updating the activity of representations in declarative memory and/or taking actions). While in others (such as EPIC) modules are arranged somewhat differently, in all cases a component can be considered a “shared resource” between two tasks if both of the tasks require engagement of
520 that component. Shared components may either be accessed by one task at a time (Fig. 1A-B) or by multiple tasks (Fig. 1C-D). It is commonly assumed that if two tasks require the same component at the same time, they interfere with one another (Fig. 1A). However, practice may result in less processing time, e.g. by compiling task processes into smaller chunks (“chunking”) [37, 138],
525 resulting in less use of that component for either of the tasks and, ultimately, improvements in multitasking through time sharing (Fig. 1B).

Connectionist models consist of multiple interconnected processing units, often grouped into modules that are used to represent and process a given type of information. Activity may be passed among units within a module, or between
530 units in different modules. Performance of a task involves the flow of activity from module(s) representing input(s) to ones representing output(s), possibly through one or more associative modules (sometimes referred to as “hidden layers”). Two tasks can be said to share a resource if their execution both make use of (i.e. have non-zero connections with) one or more of the same unit(s)
535 in a module. The representation of information within a module is generally thought of as being expressed by the pattern of activity over the processing units in that module at a given point in time. While it is theoretically possible

for this pattern of activity to represent two independent sources of information at the same time, it is often the case that the representations for different information within a module are incompatible, and therefore compete with one another (cf. Fig. 1D). Accordingly, interference can arise if two tasks make use of the same units in a module (i.e., they “share representations”) but require different representations to be active at the same time (Fig. 1C). As a practical matter—both in artificial neural networks and the brain—it can be difficult to determine exactly how information is represented in a module (i.e., the specific patterns of activity associated with each representation), and similarly the extent to which two tasks share representations. To address this, the amount of representation sharing can be quantified by correlating the average pattern of activities for pairs of tasks [45, 54, 59]. This reconceptualization of a “shared resource” has two consequences: (1) tasks may share resources in a continuous fashion, rather than sharing or not sharing a resource; and, given the capacity for learning in neural networks, (2) the extent of sharing may change over time. This suggests that improvements in multitasking may be accomplished by separating representations (resources) between tasks [54, 139] (Fig. 1D, 2D). The latter is supported by neuroimaging studies, showing that higher amounts of pattern separation between tasks predict better multitasking performance [84, 140].

Box 2: Mutual-Exclusivity and Persistence of Task Representations

Both neural networks and symbolic architectures assume that processing modules—here, defined as components that share a similar purpose (e.g. for the processing of colors)—cannot be engaged for different purposes at the same time. In neural networks, this is because two incongruent representations usually cannot be active at the same time (e.g. representing the color green and red simultaneously within a module; cf. Box 1). This notion of mutual-exclusivity applies, in principle, to all levels of representation, including incompatible rep-

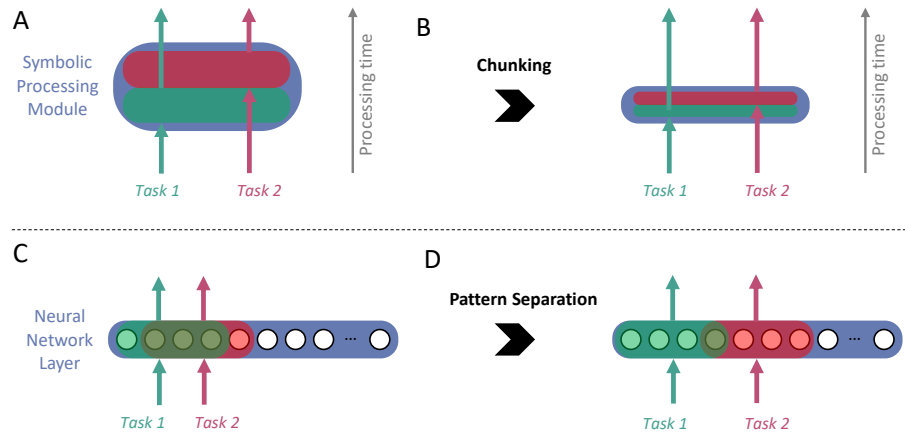


Figure Box 1.I: **Resource Sharing and Separation in Symbolic and Connectionist Models.** (A) Depiction of a resource shared between Task 1 and Task 2 in a symbolic architecture. Processing of Task 2 is delayed as long as the shared resource (shown in purple) is occupied with the processing of Task 1. (B) Improvements in multitasking can be achieved by chunking task-relevant information, leading to more efficient use of that resource [37, 138]. (C) In a connectionist model, Task 1 and Task 2 may use some of the same processing units within a module (e.g., the three units shown in dark green), leading both tasks to share a representation. (D) Improvements in multitasking can be achieved by separating representations between tasks [54, 139].

representations of task goals needed to implement cognitive control [88, 110, 141]. Symbolic architectures often take mutual-exclusivity as a given [36, 37]. In neural architectures, mutual-exclusivity can reflect the engagement of control
570 in response to the use of shared representations (see text) for the reasons explained in Box 1. Alternatively, it may be implemented locally, within a module, in the form of mutual inhibition between sets of representations. This can occur either when features have been consistently experienced to be in competition (e.g., within modules that process stimulus features; [18, 122, 142, 143]), or in
575 higher level ones (e.g., representing task goals) when this would produce competition due to the simultaneous use of shared representations [88, 110, 141]. In either case, the interaction between mutual-exclusivity and *persistence* of representations introduces a trade-off that favors either the stability or the flexibility

of representations within a module. On the one hand, if mutual-exclusivity and
 580 persistence are strong within a module, this will favor the robustness of the
 current representation, and thereby the execution of any task that depends on
 it. However, for the same reasons, it will be more difficult to switch to another
 representation (and corresponding task), owing to the greater persistence of
 the current representation and/or the greater extent to which it has suppressed
 585 the new desired representation due to mutual-exclusivity. On the other hand,
 weaker persistence and/or mutual-exclusivity, while compromising robustness,
 will make it easier to switch for reasons converse to those just stated. Thus,
 persistence coupled with mutual-exclusivity of resources between tasks—a con-
 sequence of shared representations in neural architectures—induce a tradeoff
 590 between cognitive stability (strong activation of a task-relevant representation
 to achieve high performance on a task) and cognitive flexibility (the ability to
 rapidly switch between different task representations).

Box 3: Measuring Cognitive Stability and Flexibility in the Labora-
 595 **tory**

There are multiple ways to measure cognitive stability and flexibility. Here,
 we describe how both can be operationalized in tasks that demand cognitive
 control (also see Table 1 in [117]). Perhaps the most common performance
 metric used to characterize cognitive stability is response-interference. A classic
 600 example of this is the Stroop task [144], in which participants have to name
 the color in which a word is displayed. Participants are more error-prone and
 slower to respond if the task-relevant feature (the color) and the task-irrelevant
 feature (the word) are associated with different (incongruent) responses (e.g.
 say “red” in response to the stimulus GREEN), compared to trials in which the
 605 responses associated with both features are congruent (e.g., RED). Cognitive
 stability can be assessed as the difference in error rate and/or reaction time
 between incongruent and congruent trials: The larger the congruency effect

for an individual, the lower their cognitive stability. Cognitive flexibility is commonly assessed in terms of an individual's ability to switch from one task to another (e.g. switching between naming the color and reading the word in the Stroop task). In task switching paradigms (Fig. 3.I), participants are asked either to repeat the task they performed on the previous trial (repetition trials) or to perform a different task (switch trial). The switch cost for an individual can be quantified as the difference in reaction time and/or error rate on switch trials vs. repeat trials. The switch cost is taken as an inverse measure of cognitive flexibility: the less the switch cost, the greater the cognitive flexibility. Finally, the stability-flexibility tradeoff can also be assessed in working memory tasks, in which cognitive stability is measured as the ability to actively maintain items in the presence of distractors, and cognitive flexibility is measured as ability to encode and maintain new items [145].

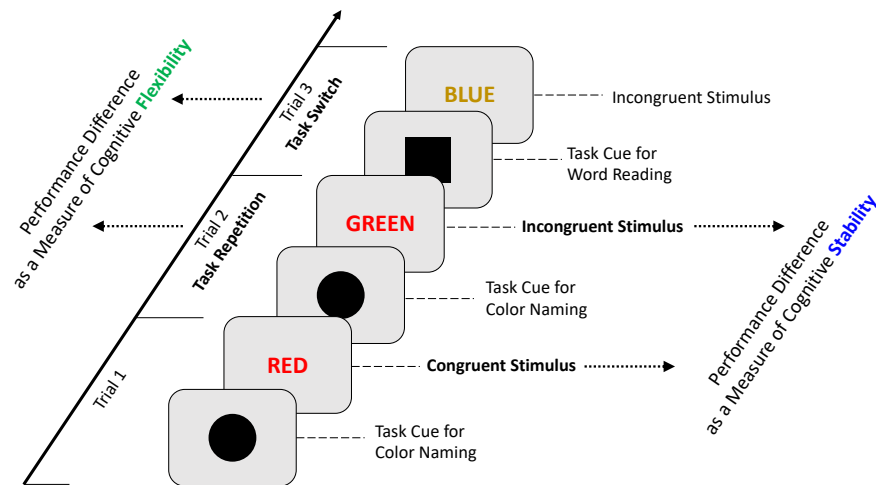


Figure Box 3.I: **Cued Task Switching Paradigm.** Each trial consists of a task cue (e.g. either a circle or a square) that instructs participants which task to perform (e.g. either color naming or word reading), followed by the stimulus to which they must respond.

Outstanding Questions

- How does the brain assess the risk of interference in the presence of shared representation, and which biophysical signals does it rely on to guide interference-free allocation of cognitive control? Moreover, how does it balance the benefits and costs of shared versus separate representation over its lifetime?
- What are the neural mechanisms that underlie improvements in our ability to multitask? Symbolic models suggest that multitasking improvements result from more efficient use of task representations and sophisticated scheduling of tasks, whereas connectionist models suggest that multitasking improvements can be achieved by separating representations between tasks. Neurophysiological and neuroimaging studies of multitask training may be useful in testing these hypotheses.
- Are there meta-control mechanisms for balancing the tradeoff between cognitive stability and flexibility, and what are their computational and neural underpinnings? Humans have been shown to adapt to changing demands for cognitive flexibility. Yet, it is still unknown what information they use to regulate this balance, how they make relevant adjustments, and over what timescale they are able to do so.
- Are there computational principles that motivate constraints on the duration of control allocation? This article focused on constraints in parallel processing (e.g., the *number* of tasks that can be performed simultaneously), and in the intensity of control allocation (i.e., to individual tasks). However, another universal observation is that control-dependent tasks are experienced as more effortful, and therefore more readily subject to fatigue, that can be thought of as the loss of intensity over time. To what

extent does this also reflect rational adaptations to fundamental computa-
tional dilemmas (such as the explore-exploit tradeoff) as opposed to lower
650 level, physical factors such as energetic or metabolic constraints?

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References

- [1] I. Koch, E. Poljac, H. Müller, A. Kiesel, Cognitive structure, flexibility,
660 and plasticity in human multitasking—an integrative review of dual-task
and task-switching research., *Psychological bulletin* 144 (6) (2018) 557.
- [2] J. D. Cohen, Cognitive control: core constructs and current considera-
tions, *The Wiley handbook of cognitive control* (2017) 1–28.
- [3] J. R. Anderson, C. J. Lebiere, The atomic components of thought, Psy-
665 chology Press, 2014.
- [4] G. Gigerenzer, Why heuristics work, *Perspectives on psychological science*
3 (1) (2008) 20–29.
- [5] R. Kurzban, A. Duckworth, J. W. Kable, J. Myers, An opportunity cost
model of subjective effort and task performance, *Behavioral and brain*
670 *sciences* 36 (6) (2013) 661–679.
- [6] F. Lieder, T. L. Griffiths, When to use which heuristic: A rational solution
to the strategy selection problem., in: *CogSci*, 2015.

- [7] H. Simon, Models of man; social and rational.
- [8] A. Shenhav, M. M. Botvinick, J. D. Cohen, The expected value of control:
 675 an integrative theory of anterior cingulate cortex function, *Neuron* 79 (2)
 (2013) 217–240.
- [9] M. Botvinick, T. Braver, Motivation and cognitive control: from behavior
 to neural mechanism, *Annual review of psychology* 66.
- [10] W. Kool, J. T. McGuire, Z. B. Rosen, M. M. Botvinick, Decision making
 680 and the avoidance of cognitive demand., *Journal of Experimental Psychol-
 ogy: General* 139 (4) (2010) 665.
- [11] I. Grahek, S. Musslick, A. Shenhav, A computational perspective on the
 roles of affect in cognitive control, *International Journal of Psychophysiol-
 ogy* 151 (2020) 25–34.
- [12] S. Musslick, A. Shenhav, M. M. Botvinick, J. D. Cohen, A computational
 685 model of control allocation based on the expected value of control, in:
 Reinforcement Learning and Decision Making Conference, 2015.
- [13] S. G. Manohar, T. T.-J. Chong, M. A. Apps, A. Batla, M. Stamelou, P. R.
 Jarman, K. P. Bhatia, M. Husain, Reward pays the cost of noise reduction
 690 in motor and cognitive control, *Current Biology* 25 (13) (2015) 1707–1716.
- [14] F. Lieder, A. Shenhav, S. Musslick, T. L. Griffiths, Rational metareasoning
 and the plasticity of cognitive control, *PLoS computational biology* 14 (4)
 (2018) e1006043.
- [15] M. K. Ho, D. Abel, J. D. Cohen, M. L. Littman, T. L. Griffiths, The
 695 efficiency of human cognition reflects planned information processing, in:
 Proceedings of the 34th AAAI Conference on Artificial Intelligence, 2020.
- [16] W. Kool, S. J. Gershman, F. A. Cushman, Cost-benefit arbitration be-
 tween multiple reinforcement-learning systems, *Psychological Science* 28
 (2017) 1321–1333.

- 700 [17] I. Grahek, A. Shenhav, S. Musslick, R. M. Krebs, E. H. Koster, Motivation
and cognitive control in depression, *Neuroscience Biobehavioral Reviews*
102 (2019) 371–381.
- [18] D. Durstewitz, J. K. Seamans, The dual-state theory of prefrontal cortex
dopamine function with relevance to catechol-o-methyltransferase geno-
705 types and schizophrenia, *Biological psychiatry* 64 (9) (2008) 739–749.
- [19] T. Goschke, Volition in action: intentions, control dilemmas and the dy-
namic regulation of intentional control, *Action science: Foundations of an*
emerging discipline (2013) 409–434.
- [20] B. Hommel, Between persistence and flexibility: The yin and yang of
710 action control, in: *Advances in motivation science*, Vol. 2, Elsevier, 2015,
pp. 33–67.
- [21] M. I. Posner, C. Snyder, Attention and cognitive control. information
processing and cognition: The loyola symposium (1975).
- [22] R. M. Shiffrin, W. Schneider, Controlled and automatic human informa-
715 tion processing: II. perceptual learning, automatic attending and a general
theory., *Psychological review* 84 (2) (1977) 127.
- [23] N. Lavie, A. Hirst, J. W. De Fockert, E. Viding, Load theory of selec-
tive attention and cognitive control., *Journal of Experimental Psychology:*
General 133 (3) (2004) 339.
- 720 [24] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, Y. Qin,
An integrated theory of the mind., *Psychological review* 111 (4) (2004)
1036.
- [25] D. Kahneman, Attention and effort, Vol. 1063, Citeseer, 1973.
- [26] H. Pashler, Dual-task interference in simple tasks: data and theory., *Psy-*
725 *chological bulletin* 116 (2) (1994) 220.

- [27] D. E. Broadbent, A mechanical model for human attention and immediate memory., *Psychological review* 64 (3) (1957) 205.
- [28] R. De Jong, Multiple bottlenecks in overlapping task performance., *Journal of Experimental Psychology: Human Perception and Performance* 19 (5) (1993) 965.
- [29] A. T. Welford, Single-channel operation in the brain, *Acta psychologica* 27 (1967) 5–22.
- [30] S. W. Keele, *Attention and human performance*, Goodyear Publishing Company, 1973.
- [31] G. D. Logan, J. Burkell, Dependence and independence in responding to double stimulation: A comparison of stop, change, and dual-task paradigms., *Journal of Experimental Psychology: Human Perception and Performance* 12 (4) (1986) 549.
- [32] D. A. Norman, D. G. Bobrow, On data-limited and resource-limited processes, *Cognitive psychology* 7 (1) (1975) 44–64.
- [33] M. Tombu, P. Jolicoeur, A central capacity sharing model of dual-task performance., *Journal of Experimental Psychology: Human Perception and Performance* 29 (1) (2003) 3.
- [34] A. Allport, B. Antonis, P. Reynolds, On the division of attention: A disproof of the single channel hypothesis, *Quarterly journal of experimental psychology* 24 (2) (1972) 225–235.
- [35] M. D. Byrne, J. R. Anderson, Serial modules in parallel: The psychological refractory period and perfect time-sharing., *Psychological Review* 108 (4) (2001) 847.
- [36] D. E. Meyer, D. E. Kieras, A computational theory of executive cognitive processes and multiple-task performance: Part i. basic mechanisms., *Psychological review* 104 (1) (1997) 3.

- [37] D. D. Salvucci, N. A. Taatgen, Threaded cognition: An integrated theory of concurrent multitasking., *Psychological review* 115 (1) (2008) 101.
- 755 [38] D. Navon, D. Gopher, On the economy of the human-processing system., *Psychological review* 86 (3) (1979) 214.
- [39] C. D. Wickens, Processing resources and attention, *Multiple-task performance* 1991 (1991) 3–34.
- 760 [40] D. E. Meyer, D. E. Kieras, A computational theory of executive cognitive processes and multiple-task performance: Part 2. accounts of psychological refractory-period phenomena., *Psychological review* 104 (4) (1997) 749.
- 765 [41] C. D. Wickens, W. Derrick, D. Berringer, J. Micalizzi, The structure of processing resources: Implications for task configuration and workload, in: *Proceedings of the Human Factors Society Annual Meeting*, Vol. 24, SAGE Publications Sage CA: Los Angeles, CA, 1980, pp. 253–256.
- 770 [42] D. P. Brumby, D. D. Salvucci, A. Howes, Focus on driving: How cognitive constraints shape the adaptation of strategy when dialing while driving, in: *Proceedings of the SIGCHI conference on human factors in computing systems*, 2009, pp. 1629–1638.
- [43] D. D. Salvucci, K. L. Macuga, Predicting the effects of cellular-phone dialing on driver performance, *Cognitive Systems Research* 3 (1) (2002) 95–102.
- 775 [44] S. F. Feng, M. Schwemmer, S. J. Gershman, J. D. Cohen, Multitasking versus multiplexing: Toward a normative account of limitations in the simultaneous execution of control-demanding behaviors, *Cognitive, Affective, & Behavioral Neuroscience* 14 (1) (2014) 129–146.
- [45] S. Musslick, B. Dey, K. Özçimder, M. Patwary, T. L. Willke, J. D. Cohen, Controlled vs. automatic processing: A graph-theoretic approach to the

- 780 analysis of serial vs. parallel processing in neural network architectures, in:
 Proceedings of the 38th Annual Meeting of the Cognitive Science Society,
 Philadelphia, PA, 2016, pp. 1547—1552.
- [46] G. Petri, S. Musslick, K. Öczimder, B. Dey, N. Ahmed, T. Willke, J. D.
 Cohen, Universal limits to parallel processing capability of network archi-
 785 tectures, *Nature Physics* (accepted for publication) arXiv:1708.03263.
- [47] N. Alon, D. Reichman, I. Shinkar, T. Wagner, S. Musslick, Cohen, J. D.,
 T. Griffiths, B. Dey, K. Öczimder, A graph-theoretic approach to multi-
 tasking. advances in neural information processing systems, in: *Advances*
in Neural Information Processing Systems, Long Beach, CA, 2017, pp.
 790 2097—2106.
- [48] A. M. Treisman, G. Gelade, A feature-integration theory of attention,
Cognitive psychology 12 (1) (1980) 97–136.
- [49] A. T. Welford, The psychological refractory period and the timing of high-
 speed performance-a review and a theory, *British Journal of Psychology*
 795 43 (1) (1952) 2.
- [50] M. C. Smith, Theories of the psychological refractory period., *Psycholog-
 ical bulletin* 67 (3) (1967) 202.
- [51] M. Kinsbourne, R. E. Hicks, Functional cerebral space: A model for over-
 flow, transfer and interference effects in human performance, *Attention*
 800 *and performance VII* (1978) 345–362.
- [52] D. Navon, J. Miller, Role of outcome conflict in dual-task interference.,
Journal of Experimental Psychology: Human Perception and Performance
 13 (3) (1987) 435.
- [53] G. D. Logan, Attention in character-classification tasks: Evidence for the
 805 automaticity of component stages., *Journal of Experimental Psychology:
 General* 107 (1) (1978) 32.

- [54] S. Musslick, A. Saxe, A. N. Hoskin, D. Reichman, J. D. Cohen, On the rational boundedness of cognitive control: Shared versus separated representations (2020) PsyArXiv: <https://doi.org/10.31234/osf.io/jkhdf>.
- 810 [55] A. M. Albers, P. Kok, I. Toni, H. C. Dijkerman, F. P. De Lange, Shared representations for working memory and mental imagery in early visual cortex, *Current Biology* 23 (15) (2013) 1427–1431.
- [56] E. Froudarakis, U. Cohen, M. Diamantaki, E. Y. Walker, J. Reimer, P. Berens, H. Sompolinsky, A. S. Tolias, Object manifold geometry across
815 the mouse cortical visual hierarchy, *bioRxiv*.
- [57] W. Notebaert, W. Gevers, T. Verguts, W. Fias, Shared spatial representations for numbers and space: the reversal of the snarc and the simon effects., *Journal of Experimental Psychology: Human Perception and Performance* 32 (5) (2006) 1197.
- 820 [58] K. Weber, M. H. Christiansen, K. M. Petersson, P. Indefrey, P. Hagoort, fmri syntactic and lexical repetition effects reveal the initial stages of learning a new language, *Journal of Neuroscience* 36 (26) (2016) 6872–6880.
- [59] T. T. Rogers, J. L. McClelland, *Semantic cognition: A parallel distributed processing approach*, MIT press, 2004.
825
- [60] J. Decety, J. A. Sommerville, Shared representations between self and other: a social cognitive neuroscience view, *Trends in cognitive sciences* 7 (12) (2003) 527–533.
- [61] G. E. Hinton, et al., Learning distributed representations of concepts,
830 in: *Proceedings of the eighth annual conference of the cognitive science society*, Vol. 1, Amherst, MA, 1986, p. 12.
- [62] D. E. Rumelhart, P. M. Todd, et al., Learning and connectionist representations, *Attention and performance XIV: Synergies in experimental*

- psychology, artificial intelligence, and cognitive neuroscience 2 (1993) 3–30.
- [63] A. M. Saxe, J. L. McClelland, S. Ganguli, A mathematical theory of semantic development in deep neural networks, *Proceedings of the National Academy of Sciences* 116 (23) (2019) 11537–11546.
- [64] G. R. Yang, M. R. Joglekar, H. F. Song, W. T. Newsome, X.-J. Wang, Task representations in neural networks trained to perform many cognitive tasks, *Nature neuroscience* 22 (2) (2019) 297–306.
- [65] S. Musslick, A. Saxe, K. Özçimder, B. Dey, G. Henselman, J. D. Cohen, Multitasking capability versus learning efficiency in neural network architectures, in: *Proceedings of the 39th Annual Meeting of the Cognitive Science Society*, London, UK, 2017, pp. 829–834.
- [66] R. L. Jackson, T. T. Rogers, M. A. L. Ralph, Reverse-engineering the cortical architecture for controlled semantic cognition, *bioRxiv* (2019) 860528.
- [67] S. M. Frankland, J. D. Greene, Concepts and compositionality: in search of the brain’s language of thought, *Annual review of psychology* 71 (2020) 273–303.
- [68] S. Ravi, S. Musslick, M. Hamin, T. Willke, J. D. Cohen, Navigating the tradeoff between multi-task learning and learning to multitask in deep neural networks, *arXiv* (2020) 2007.10527.
- [69] R. Caruana, Multitask learning, *Machine learning* 28 (1) (1997) 41–75.
- [70] A. Maurer, M. Pontil, B. Romera-Paredes, The benefit of multitask representation learning, *The Journal of Machine Learning Research* 17 (1) (2016) 2853–2884.
- [71] T. Flesch, J. Balaguer, R. Dekker, H. Nili, C. Summerfield, Comparing continual task learning in minds and machines, *Proceedings of the National Academy of Sciences* 115 (44) (2018) E10313–E10322.

- [72] M. Long, J. Wang, Learning multiple tasks with deep relationship networks, arXiv preprint arXiv:1506.02117 2 (2015) 1.
- [73] X. Lu, X. Li, L. Mou, Semi-supervised multitask learning for scene recognition, IEEE transactions on cybernetics 45 (9) (2014) 1967–1976.
- 865 [74] R. Collobert, J. Weston, A unified architecture for natural language processing: Deep neural networks with multitask learning, in: Proceedings of the 25th international conference on Machine learning, 2008, pp. 160–167.
- [75] B. McCann, N. S. Keskar, C. Xiong, R. Socher, The natural language decathlon: Multitask learning as question answering, arXiv preprint
870 arXiv:1806.08730.
- [76] L. Deng, G. Hinton, B. Kingsbury, New types of deep neural network learning for speech recognition and related applications: An overview, in: 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, IEEE, 2013, pp. 8599–8603.
- 875 [77] T. Goschke, Intentional reconfiguration and j-ti involuntary persistence in task set switching, Control of cognitive processes: Attention and performance XVIII 18 (2000) 331.
- [78] T. Verguts, Binding by random bursts: A computational model of cognitive control, Journal of Cognitive Neuroscience 29 (6) (2017) 1103–1118.
- 880 [79] H. Ruge, U. Wolfensteller, Rapid formation of pragmatic rule representations in the human brain during instruction-based learning, Cerebral Cortex 20 (7) (2010) 1656–1667.
- [80] J. D. Cohen, K. Dunbar, J. L. McClelland, On the control of automatic processes: a parallel distributed processing account of the stroop effect.,
885 Psychological review 97 (3) (1990) 332.
- [81] M. M. Botvinick, T. S. Braver, D. M. Barch, C. S. Carter, J. D. Cohen, Conflict monitoring and cognitive control., Psychological review 108 (3) (2001) 624.

- [82] D. Badre, A. Bhandari, H. Keglovits, A. Kikumoto, The dimensionality
890 of neural representations for control.
- [83] Y. Sagiv, S. Musslick, Y. Niv, J. D. Cohen, Efficiency of learning vs.
processing: Towards a normative theory of multitasking, in: Proceedings
of the 40th Annual Meeting of the Cognitive Science Society, Madison,
WI, 2018, pp. 1004—1009, arXiv:2007.03124.
- 895 [84] K. Garner, P. E. Dux, Training conquers multitasking costs by dividing
task representations in the frontoparietal-subcortical system, Proceedings
of the National Academy of Sciences 112 (46) (2015) 14372–14377.
- [85] E. K. Miller, J. D. Cohen, An integrative theory of prefrontal cortex func-
tion, Annual review of neuroscience 24 (1) (2001) 167–202.
- 900 [86] F. Bouchacourt, T. J. Buschman, A flexible model of working memory,
Neuron 103 (1) (2019) 147–160.
- [87] K. Oberauer, R. Kliegl, A formal model of capacity limits in working
memory, Journal of memory and language 55 (4) (2006) 601–626.
- [88] M. Usher, J. D. Cohen, Short term memory and selection processes in
905 a frontal-lobe model, in: Connectionist models in cognitive neuroscience,
Springer, 1999, pp. 78–91.
- [89] K. Oberauer, S. Farrell, C. Jarrold, S. Lewandowsky, What limits working
memory capacity?, Psychological Bulletin 142 (7) (2016) 758.
- [90] A. M. Treisman, The binding problem, Current opinion in neurobiology
910 6 (2) (1996) 171–178.
- [91] I. Biederman, Recognition-by-components: a theory of human image un-
derstanding., Psychological review 94 (2) (1987) 115.
- [92] G. D. Logan, R. D. Gordon, Executive control of visual attention in dual-
task situations., Psychological review 108 (2) (2001) 393.

- 915 [93] H. B. Barlow, Single units and sensation: a neuron doctrine for perceptual psychology?, *Perception* 1 (4) (1972) 371–394.
- [94] M. Riesenhuber, T. Poggio, Are cortical models really bound by the “binding problem”?, *Neuron* 24 (1) (1999) 87–93.
- [95] J. C. Liang, J. Erez, F. Zhang, R. Cusack, M. D. Barense, Experience
920 transforms conjunctive object representations: Neural evidence for unitization after visual expertise, *Cerebral Cortex* 30 (5) (2020) 2721–2739.
- [96] R. Desimone, Face-selective cells in the temporal cortex of monkeys, *Journal of cognitive neuroscience* 3 (1) (1991) 1–8.
- [97] K. Tanaka, Inferotemporal cortex and object vision, *Annual review of neuroscience* 19 (1) (1996) 109–139.
925
- [98] M. Eickenberg, A. Gramfort, G. Varoquaux, B. Thirion, Seeing it all: Convolutional network layers map the function of the human visual system, *NeuroImage* 152 (2017) 184–194.
- [99] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, *nature* 521 (7553) (2015) 436–444.
930
- [100] J. Schmidhuber, Deep learning in neural networks: An overview, *Neural networks* 61 (2015) 85–117.
- [101] G. Dreisbach, J. Müller, T. Goschke, A. Strobel, K. Schulze, K.-P. Lesch, B. Brocke, Dopamine and cognitive control: the influence of spontaneous
935 eyeblink rate and dopamine gene polymorphisms on perseveration and distractibility., *Behavioral neuroscience* 119 (2) (2005) 483.
- [102] I. J. Tharp, A. D. Pickering, Individual differences in cognitive-flexibility: The influence of spontaneous eyeblink rate, trait psychoticism and working memory on attentional set-shifting, *Brain and cognition* 75 (2) (2011) 119–
940 125.

- [103] H. Zhang, D. K.-S. Chan, Regulatory focus influences perseveration and distractibility in task switching, *Psychological research* 77 (6) (2013) 808–817.
- [104] H. Crofts, J. Dalley, P. Collins, J. Van Denderen, B. Everitt, T. Robbins, A. Roberts, Differential effects of 6-ohda lesions of the frontal cortex and caudate nucleus on the ability to acquire an attentional set, *Cerebral cortex* 11 (11) (2001) 1015–1026.
- [105] R. Cools, M. J. Frank, S. E. Gibbs, A. Miyakawa, W. Jagust, M. D’Esposito, Striatal dopamine predicts outcome-specific reversal learning and its sensitivity to dopaminergic drug administration, *Journal of Neuroscience* 29 (5) (2009) 1538–1543.
- [106] G. Dreisbach, How positive affect modulates cognitive control: The costs and benefits of reduced maintenance capability, *Brain and cognition* 60 (1) (2006) 11–19.
- [107] G. Dreisbach, T. Goschke, How positive affect modulates cognitive control: reduced perseveration at the cost of increased distractibility., *Journal of Experimental Psychology: Learning, Memory, and Cognition* 30 (2) (2004) 343.
- [108] N. C. van Wouwe, G. P. Band, K. R. Ridderinkhof, Positive affect modulates flexibility and evaluative control, *Journal of Cognitive Neuroscience* 23 (3) (2011) 524–539.
- [109] R. Cools, Chemistry of the adaptive mind: Lessons from dopamine, *Neuron* 104 (1) (2019) 113–131.
- [110] K. Ueltzhöffer, D. J. Armbruster-Genç, C. J. Fiebach, Stochastic dynamics underlying cognitive stability and flexibility, *PLoS computational biology* 11 (6).
- [111] S. Musslick, J. S. Jang, M. Shvartsman, A. Shenhav, J. D. Cohen, Constraints associated with cognitive control and the stability-flexibility

- dilemma, in: Proceedings of the 40th Annual Meeting of the Cognitive Science Society, Madison, WI, 2018, pp. 806—811.
- [112] S. Musslick, A. Bizyaeva, S. Agaron, E. L. Naomi, J. D. Cohen, Stability-flexibility dilemma in cognitive control: A dynamical system perspective, in: Proceedings of the 41st Annual Meeting of the Cognitive Science Society, Montreal, CA, 2019, pp. 2420—2426.
- [113] T. S. Braver, D. M. Barch, J. D. Cohen, Cognition and control in schizophrenia: a computational model of dopamine and prefrontal function, *Biological psychiatry* 46 (3) (1999) 312–328.
- [114] R. C. O'Reilly, M. J. Frank, Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia, *Neural computation* 18 (2) (2006) 283–328.
- [115] S. A. Herd, T. E. Hazy, C. H. Chatham, A. M. Brant, N. P. Friedman, et al., A neural network model of individual differences in task switching abilities, *Neuropsychologia* 62 (2014) 375–389.
- [116] S. Braem, Conditioning task switching behavior, *Cognition* 166 (2017) 272–276.
- [117] G. Dreisbach, K. Fröber, On how to be flexible (or not): Modulation of the stability-flexibility balance, *Current Directions in Psychological Science* 28 (1) (2019) 3–9.
- [118] U. Mayr, What matters in the cued task-switching paradigm: Tasks or cues?, *Psychonomic bulletin & review* 13 (5) (2006) 794–799.
- [119] S. Monsell, G. A. Mizon, Can the task-cuing paradigm measure an endogenous task-set reconfiguration process?, *Journal of Experimental Psychology: Human Perception and Performance* 32 (3) (2006) 493.
- [120] A. Siqu-Liu, T. Egner, Contextual adaptation of cognitive flexibility is driven by task-and item-level learning.

- [121] C. Liu, N. Yeung, Dissociating expectancy-based and experience-based control in task switching., *Journal of Experimental Psychology: Human Perception and Performance* 46 (2) (2020) 131.
- 1000 [122] M. F. Panichello, B. DePasquale, J. W. Pillow, T. J. Buschman, Error-correcting dynamics in visual working memory, *Nature communications* 10 (1) (2019) 1–11.
- [123] L. M. McTeague, M. S. Goodkind, A. Etkin, Transdiagnostic impairment of cognitive control in mental illness, *Journal of psychiatric research* 83 (2016) 37–46.
- 1005 [124] R. Cools, A. Miyakawa, M. Sheridan, M. D’Esposito, Enhanced frontal function in parkinson’s disease, *Brain* 133 (1) (2010) 225–233.
- [125] A. A. Moustafa, S. J. Sherman, M. J. Frank, A dopaminergic basis for working memory, learning and attentional shifting in parkinsonism, *Neuropsychologia* 46 (13) (2008) 3144–3156.
- 1010 [126] U. Frith, *Autism: Explaining the enigma*, Blackwell Publishing, 2003.
- [127] K. C. Plaisted, Reduced generalization in autism: An alternative to weak central coherence.
- [128] R. M. Joseph, B. Keehn, C. Connolly, J. M. Wolfe, T. S. Horowitz, Why is visual search superior in autism spectrum disorder?, *Developmental science* 12 (6) (2009) 1083–1096.
- 1015 [129] S. Baldassi, F. Pei, N. Megna, G. Recupero, M. Viespoli, R. Igliozi, R. Tancredi, F. Muratori, G. Cioni, Search superiority in autism within, but not outside the crowding regime, *Vision research* 49 (16) (2009) 2151–2156.
- 1020 [130] K. Plaisted, M. O’Riordan, S. Baron-Cohen, Enhanced visual search for a conjunctive target in autism: A research note, *The Journal of Child Psychology and Psychiatry and Allied Disciplines* 39 (5) (1998) 777–783.

- [131] J. L. McClelland, The basis of hyperspecificity in autism: A preliminary suggestion based on properties of neural nets, *Journal of Autism and Developmental Disorders* 30 (5) (2000) 497–502.
- [132] M. Del Giudice, B. J. Crespi, Basic functional trade-offs in cognition: An integrative framework, *Cognition* 179 (2018) 56–70.
- [133] J. A. Masis, T. Chapman, J. Y. Rhee, D. D. Cox, A. M. Saxe, Rats strategically manage learning during perceptual decision making, *bioRxiv*.
- [134] J. D. Cohen, S. M. McClure, A. J. Yu, Should i stay or should i go? how the human brain manages the trade-off between exploitation and exploration, *Philosophical Transactions of the Royal Society B: Biological Sciences* 362 (1481) (2007) 933–942.
- [135] A. Geana, R. Wilson, N. D. Daw, J. D. Cohen, Boredom, information-seeking and exploration., in: *CogSci*, 2016.
- [136] J. Schmidhuber, A possibility for implementing curiosity and boredom in model-building neural controllers, in: *Proc. of the international conference on simulation of adaptive behavior: From animals to animats*, 1991, pp. 222–227.
- [137] M. Agrawal, M. G. Mattar, J. D. Cohen, N. D. Daw, The temporal dynamics of opportunity costs: A normative account of cognitive fatigue and boredom, *bioRxiv*.
- [138] N. A. Taatgen, F. J. Lee, Production compilation: A simple mechanism to model complex skill acquisition, *Human Factors* 45 (1) (2003) 61–76.
- [139] S. Musslick, Cohen, J. D., A mechanistic account of constraints on control-dependent processing: Shared representation, conflict and persistence, in: *Proceedings of the 41st Annual Meeting of the Cognitive Science Society*, Montreal, CA, 2019, pp. 849–855.

- [140] M. Nijboer, J. Borst, H. van Rijn, N. Taatgen, Single-task fmri overlap
1050 predicts concurrent multitasking interference, *NeuroImage* 100 (2014) 60–
74.
- [141] E. Kalanthroff, E. J. Davelaar, A. Henik, L. Goldfarb, M. Usher, Task
conflict and proactive control: A computational theory of the stroop task.,
Psychological review 125 (1) (2018) 59.
- 1055 [142] R. C. O'Reilly, T. E. Hazy, S. A. Herd, The leabra cognitive architecture:
How to play 20 principles with nature, *The Oxford handbook of cognitive
science* 91 (2016) 91–116.
- [143] M. Usher, J. L. McClelland, The time course of perceptual choice: the
leaky, competing accumulator model., *Psychological review* 108 (3) (2001)
1060 550.
- [144] J. R. Stroop, Studies of interference in serial verbal reactions., *Journal of
experimental psychology* 18 (6) (1935) 643.
- [145] D. Papadopetraki, M. I. Froboese, A. Westbrook, B. B. Zandbelt,
R. Cools, Quantifying the cost of cognitive stability and flexibility, *bioRxiv*
1065 (2019) 743120.