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Linking Computational Models of Two Core Tasks of Cognitive Control

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Abstract

Cognitive control refers to the ability to maintain goal-relevant information in the face of distraction, making it a core construct for understanding human thought and behavior. There is great theoretical and practical value in building theories that can be used to explain or to predict variations in cognitive control as a function of experimental manipulations or individual differences. A critical step toward building such theories is determining which latent constructs are shared between laboratory tasks that are designed to measure cognitive control. In the current work, we examine this question in a novel way by formally linking computational models of two canonical cognitive control tasks, the Eriksen flanker and task-switching task. Specifically, we examine whether model parameters that capture cognitive control processes in one task can be swapped across models to make predictions about individual differences in performance on another task. We apply our modeling and analysis to a large scale data set from an online cognitive training platform, which optimizes our ability to detect individual differences in the data. Our results suggest that the flanker and task-switching tasks probe common control processes. This finding supports the view that higher level cognitive control processes as opposed to solely strategies in speed and accuracy tradeoffs, or perceptual processing and motor response speed are shared across the two tasks. We discuss how our computational modeling substitution approach addresses limitations of prior efforts to relate performance across different cognitive control tasks, and how our findings inform current theories of cognitive control.

Keywords

theories of cognitive control; linking models of cognition; Eriksen flanker task; task-switching task; cognitive training

Goal directed thought is a defining feature of human phenomenology and action. Fundamental to goal-directed thought is *cognitive control,* which is, broadly, a construct

that describes people's capacity to prioritize goal-relevant information and deprioritize goal-irrelevant information (Botvinick et al., 2001; Dreher & Berman, 2002; Miller, 2000). Because of its close link to goal-directed thought, there is great theoretical and practical value in building theories that can be used to explain, or predict changes in cognitive control as a function of experimental manipulations or individual differences.

A critical part of building such theories is determining which, if any, common latent constructs are engaged in different cognitive control tasks. Such work provides insight into a long-standing debate regarding whether there are domain-general control processes, implying that a single control system supports performance across different task demands (e.g., Rajah et al., 2008), or domain-specific control processes, implying that there are multiple, independent cognitive control systems that are only engaged within, but not across tasks (e.g., Akçay & Hazeltine, 2011; Egner et al., 2007).

More broadly, relating performance across different control tasks aligns with a fundamental goal of social and cognitive scientists, which is to develop theories that can generalize across different laboratory tasks and, ultimately, to phenomena observed in more ecological settings (e.g., J. R. Anderson et al., 2004; Lee, 2011; Newell, 1994). A basic step toward developing such theories is discovering invariants across experimental tasks. Determining which latent processes are shared across tasks turns out to be quite challenging, however. That is, despite the fact that many theories in psychology are designed to capture common processes across a variety of tasks, they may fail to do so in practice (Yarkoni, 2022). As pointed out by several researchers (B. Anderson, 2011; Di Lollo, 2018; Hommel et al., 2019), attention is a good example of such a construct because it is used to explain performance across a variety of tasks, but there is little mainstream consensus regarding which attentional paradigms probe the same latent variable.

The first challenge researchers face when linking performance across tasks, is measuring key hypothetical constructs. Although this is a well-known challenge for social science researchers in general (e.g., Borsboom et al., 2004; Brady et al., 2021; Kellen et al., 2020; Meehl, 1967; Regenwetter & Robinson, 2017; Rotello et al., 2015), it is also a challenge for researchers who study cognitive control in particular, because the dominant measurement approach called the *subtraction method* is known to suffer from major limitations. These limitations have been discussed in detail by other researchers and will be reviewed later in this article. For now, we simply note that the subtraction method may not yield a process pure measure of cognitive control, meaning that it may confound cognitive control with other processes such as individual differences in speed and accuracy tradeoffs (e.g., Draheim et al., 2019; Hedge et al., 2021), or perceptual processing and motor response speed (e.g., Frischkorn & Schubert, 2018). For these reasons, the subtraction method cannot serve as a basis for inferring which processes are shared across cognitive control tasks.

A second challenge researchers face is in selecting rigorous methods for determining whether latent constructs are invariant across tasks. That is, verbal theories or intuition are not an optimal test bed for whether two models of different tasks capture the same latent constructs, just like they may not serve as rigorous measurement tools of the latent

constructs themselves. A preferred approach, which we discuss here, is to use quantitative methods to formally link cognitive models.

A final challenge for linking performance across cognitive control tasks in particular, is obtaining samples that are sufficiently large and heterogeneous, such that stable individual differences in performance across tasks are detectable (e.g., Cronbach & Furby, 1970). This criterion can be difficult to meet, particularly for cognitive psychologists who mainly work with undergraduate student samples, which are often relatively small and homogeneous (Henrich et al., 2010; Peterson & Merunka, 2014).

Our work attempts to address these issues. To this end, we use novel computational models of two canonical cognitive control tasks, the Eriksen flanker (B. A. Eriksen & Eriksen, 1974) and task-switching task (Jersild, 1927; Monsell, 2003), to formally test the hypothesis that common cognitive control processes are engaged across these two tasks. The task-switching model is based on a variant developed by Steyvers et al. (2019), whereas the flanker model was newly developed for the current work.

The main advantage of using a computational modeling is that it forces precise definition of key hypothetical constructs in a way that noncomputational modeling approaches, or verbal theories may not (e.g., Borsboom et al., 2021; Farrell & Lewandowsky, 2010; Grahek et al., 2020; Guest & Martin, 2020; Jones et al., 2014; Lewandowsky & Farrell, 2010; Navarro, 2020; Robinaugh et al., 2021). Our task models combine perceptual processing speed and cognitive control with evidence accumulator models (Batchelder et al., 2016; Ratcliff et al., 2016). This modeling framework provides a way of decomposing lower level processes, such as speed of perceptual decision processes from cognitive control processes, while jointly modeling response times and responses choices. As such, the current modeling approach circumvents the core measurement issues of the subtraction method.

We formally link cognitive models of the flanker and task-switching tasks by testing whether we can make predictions about individual differences in performance on one task, using parameters that capture cognitive control processes estimated from a different task. More precisely, we assess whether cognitive control parameters from models of the two tasks can be swapped between models to make predictions about individual differences in performance. For illustration, suppose Bill and Sue are two individuals who participate in both tasks. We explore the following questions: *Can Bill's cognitive control parameters from the flanker model be used in the model for task-switching to predict his task-switching behavior? How does that prediction compare to the situation where we use Sue's parameters from the flanker model to predict Bill's task-switching behavior?*

Finally, we apply our modeling to a large scale data set taken from Lumosity, a popular online cognitive training platform. Previous work used Lumosity samples of data to examine the effects of age and performance quality on dropout rates in cognitive training tasks (Steyvers & Benjamin, 2019), the relationship between age and training on task-switching performance (Steyvers et al., 2019), and the latent structure of learning trajectories across different cognitive tasks (Steyvers & Schafer, 2020). One major appeal of using a Lumosity sample is that users are more likely to be intrinsically motivated to perform each of the tasks

because they may operate under the assumption that it provides a form of cognitive training. Moreover, a wide range of users train on different tasks and typically do so anywhere from several months up to several years.

Our sample consists of approximately 500 adults who range in age from 21 to 80 years of age. Therefore, our sample is heterogeneous as well as large at the level of individuals and trials, optimizing our ability to detect individual differences in the data. Furthermore, we capitalize on the fact that individuals in our sample trained on both cognitive control tasks up to several years by testing an extension of our models that capture the change in cognitive control dynamics as a function of training. For ease of exposition, we focus on the core cognitive control models of each task in the main text, and discuss the extensions of these models, which capture effects of learning in Appendix D. All of our data and code can be accessed through the Open Science Framework Repository at the following link: https://osf.io/6hjwv/.

To preview our results, we find evidence for the domain-general view that cognitive control processes are shared across tasks. In particular, we find that model parameters that capture cognitive control processes in one task, can be used to make predictions of individual differences in performance on a different cognitive control task. To our knowledge, our work is the first to show evidence for the domain-general view of cognitive control by formally linking computational models of control tasks, an approach we summarize next.

Overview of Analytic Approach

Before discussing details of the cognitive control tasks and models, we provide a conceptual overview of our analytic approach and describe how it contrasts to a few alternative approaches toward modeling performance within and across cognitive tasks. We refer to our approach as *parameter substitution analysis* because we directly substitute parameters across models of two cognitive control tasks to make predictions about performance on each of the tasks.

Our parameter substitution analysis contrasts with the mainstream modeling approach in which task-specific models are evaluated only within each task, without attempts to formally relate models of different tasks. The majority of modeling efforts in computational social sciences fall in the latter category (e.g., Servant & Logan, 2019; Steyvers et al., 2019; White et al., 2011), likely because researchers tend to focus on explaining performance within tasks (e.g., Yarkoni & Westfall, 2017) or rely mainly on verbal theories to relate performance across tasks, but also because task-specific models may lay the groundwork for integrative theories.

As part of the parameter substitution approach we treat one of the tasks as a *source task* and the other task as a *target task*. The source task refers to the task from which model parameters are estimated using the data and model for that task. The target task refers to the task to which model parameters from the source task are generalized.

Recalling our example of Bill and Sue, we assume that the source task is the flanker task, and we fit the flanker model separately to Bill's and Sue's flanker data to obtain a set

of best-fitting parameters for Bill and a different set of best-fitting parameters for Sue. Both sets of parameters are assumed to capture different processes; for instance, one set of parameters quantifies perceptual processing and motor response speed, whereas another set quantifies cognitive control processes. After obtaining best-fitting parameters from Bill's and Sue's flanker data, we substitute these parameters into the model from the target task to predict the target task data for Bill and Sue. In this example, the target model is the task-switching model and we use it to predict Bill's and Sue's task-switching data. Importantly, our parameter substitution is guided in a top–down way, meaning that we use a priori, theoretically grounded predictions regarding which model parameters from the source task should replace parameters in the model from the target task.

We can test key hypotheses by evaluating the predictive accuracy of the target model by substituting parameters in different ways, with different model variants. We flesh out this analysis and central predictions later in the article. For the purposes of this illustration, we note that evidence for the domain-general view of cognitive control would be reflected in the result that cognitive control parameters estimated from the data in the source task can be used to predict individual differences in behavior on the target task.

Comparison to Other Linking Approaches

Conceptually, the parameter substitution approach is most similar to the directed modeling approach (Turner et al., 2017, 2019; Wong & Wang, 2006), which is used to constrain behavioral models with neural models and data, or vice versa. For instance, researchers use parameters from a neural model to constrain parameters in a behavioral model to test various linking propositions regarding how neural processes map onto behavioral phenomena. One difference between this and our approach is that we use different cognitive models to examine relationships across behavioral tasks, rather than a neural and cognitive model to examine relationships between neural processes and behavioral phenomena.

The parameter substitution analysis is one of several tools that could be used to link cognitive models of different tasks. For instance, it contrasts to hierarchical Bayesian modeling analyses, in which models are jointly fit to data from two different tasks (e.g., Cox et al., 2018). One advantage of using a parameter substitution analysis over hierarchical Bayesian joint modeling, is that the substitution approach is computationally simple. For instance, it does not require specifying a covariance matrix that captures correlations between parameters, which can be computationally difficult and relatively inefficient to estimate (e.g., Galdo et al., 2020; Turner, Forstmann, et al., 2013).

Moreover, parameter substitution meets one of the highest benchmark for evaluating the *generalizability,* or predictive ability of cognitive models (Browne, 2000; Busemeyer & Wang, 2000) because it involves predicting individual and trial-level data on a new task. This contrasts with other tests of model generalizability, such as those used in joint modeling approaches that use within-task cross-validation (e.g., Turner, Forstmann, et al., 2013). Within-task cross-validation, involves predicting missing, or "held-out" data on the same task, rather than predicting performance on a completely different task. As we elaborate on in the General Discussion section, each type of analysis can be used to address somewhat

different research questions, and we view our analysis and findings as the groundwork for future computational efforts.

Finally, parameter substitution contrasts with integrative modeling approaches (Palestro et al., 2018), in which a single cognitive architecture is used to explain performance across tasks. An example of such a modeling framework is Adaptive Control of Thought-Rational (ACT-R; e.g., J. R. Anderson et al., 2004), a unifying model of higher level cognitive processes. The ACT-R model consists of different modules that represent core cognitive processes such as distinct memory buffers for different types of sensory inputs. The demands of a task determine inputs to these modules, and the outputs of these modules are combined to yield predictions about responses within a task.

Unlike the mainstream modeling approach in which cognitive models of different tasks are not linked with one another, the integrative approach formally unifies theories of different tasks. Unlike the parameter substitution or joint modeling approaches, the integrative approach uses a single, rather than distinct task models to explain performance across tasks (for other examples see: Bundesen, 1990; Hintzman, 1986; Logan, 2002; Murdock, 1995; Shiffrin & Steyvers, 1997). A potential challenge for developing integrative models is that they force strong assumptions regarding how processing dynamics are engaged across tasks (Palestro et al., 2018). The current project can be seen as the basis for developing integrative models of these two tasks, or for constraining existing models. In the following sections, we describe the two core cognitive control tasks.

Two Canonical Tasks of Cognitive Control

The task-switching and Eriksen flanker are two of the most well-known tasks designed to measure cognitive control (B. A. Eriksen & Eriksen, 1974; Monsell, 2003). Importantly, these two tasks have different structures. The task-switching task is commonly construed as measuring the ability to flexibly and efficiently switch between task goals (e.g., Von Bastian & Druey, 2017), whereas the flanker task is commonly construed as measuring inhibition (e.g., Erb et al., 2020; Heil et al., 2000). Despite their structural differences both tasks provide potentially different ways of measuring individual differences in attentional control (e.g., Munakata et al., 2011), that is, the ability to prioritize task-relevant information and/or inhibit task-irrelevant information.

In the following sections, we describe generic and Lumosity versions of each task. We also review some of the extensive behavioral and modeling literature on these tasks. Our review is not intended to be exhaustive, but to provide a coarse overview on the diversity of theoretical advances in understanding task-switching and flanker effects.

Task-Switching Lumosity Task

In generic versions of the task-switching task people are shown a stimulus and are cued to evaluate and respond to the stimulus in a certain way. The specific way in which people are instructed to evaluate and respond to each stimulus defines the stimulus–response (S-R) task (Monsell, 1996), which may vary, often unpredictably, in a trial-by-trial fashion. For instance, in the Lumosity version of the task-switching task people are shown leaves that

are pointing in ones of four directions (left, right, up or down) and moving in one of four directions (left, right, up or down; upper panel of Figure 1). On each trial, people are cued by the color of the leaf and a written prompt to quickly respond either on the pointing direction or the moving direction of the leaf. For instance, if the leaf is orange people must respond on the movement direction of the leaf.

A typical finding in the task-switching paradigm is a task-switching cost, which is depicted for reaction times (RTs) and error rates in Figure 1. Specifically, on the first trial after a task switch, such as a switch between the moving and pointing tasks, people are slower and make more errors on the currently cued task. These task-switching costs are usually quantified via subtraction methods, by taking the difference in reaction times or accuracy on the first trial of a task-switch and baseline performance on this task (e.g., taken from repeat trials). The size of the task-switching cost is interpreted as an index of how effectively people are able to either prioritize task-relevant information of the cued task, or suppress task-irrelevant information from the uncued task, or some combination of both (e.g., Kiesel et al., 2010; Rubinstein et al., 2001).

Previous Theories and Models of Task-Switching Effects

A shared assumption of mainstream theories of task-switching is that, when completing tasks, people form a mental *task set,* or a structured representation of the relevant stimulus–response mappings (Monsell, 1996). The primary aim in this literature is to illuminate the processing dynamics that lead to effective and efficient task-set *reconfiguration*[1] that is, switching between mental task sets.

One facet of task-set reconfiguration is preparation for the currently cued task. In behavioral studies, effects of task-set preparation are often studied by varying the temporal interval before a task switch. In unpredictable task sequences, this temporal interval is coupled with an explicit task cue, which signals the upcoming task before a stimulus is presented (Meiran, 1996). For instance, if participants are instructed to respond to the parity of a number on Task 1 and the magnitude of the number on Task 2, the task cue would signal which task is relevant on a given trial before the number is shown—varying the cue stimulus interval (CSI) gives people more or less time to prepare for the upcoming task. Typically, increasing the CSI reduces switch costs, although it does not eliminate them (Koch & Allport, 2006; Meiran, 1996; Monsell & Mizon, 2006). This evidence suggests that preparation prior to stimulus onset plays a partial role in effective task-set reconfiguration.

In addition to having enough time to prepare the currently cued task set, people must also effectively inhibit the currently uncued task set. In support of this view, Allport et al. (1994) found asymmetric switch costs in a Stroop variant of the task-switching task; in this task, switch costs were larger when participants switched from the color-naming task to the word-reading task than vice versa. Because word reading dominates color-naming in the Stroop task (Stroop, 1935), this result implies that there is a larger task-switching cost when switching from a difficult to an easier task. This pattern of results is hard to explain with a task-preparation account, which should predict that a dominant task set should be easier to

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[1]Here we use "reconfiguration" in the broad sense that encompasses both proactive and reactive processes (as in Koch et al., 2018).

prepare than a less dominant one. Allport et al., proposed that the color-naming task requires more inhibition of the dominant word-reading tasks, than the reverse; when switching to the easier word-reading task, these effects of increased inhibition carryover, leading to a larger switch cost. Finally, in support of task set carry over effects, Allport et al.'s reported item-specific switch costs, the finding that switch costs are larger when the same stimuli are shown on preswitch and switch trials.

Together, behavioral evidence indicates that task-set reconfiguration is a multicomponent process, and a variety of computational models were developed to explain its dynamics. For instance, Logan and Gordon (2001) proposed a model of executive control, according to which a task set is defined it two ways. At a high level, task sets are propositions that represent task instructions. At a subordinate level, task sets are instantiated as parameters that determine how stimuli are evaluated and responded to within specific tasks; each task may differ in the number of parameters it requires for completion, as well as the values of those parameters. Within this framework, switch costs reflect the time it takes for the central executive to update and transmit a task's parameter settings from higher level to subordinate processes.

Gilbert and Shallice (2002) took an alternative modeling approach and proposed a parallel distributed processing model (based on work by Cohen et al., 1990; Cohen & Huston, 1994). In this model, each task is represented with a separate pathway, which is a set of input and output nodes and connections between them. Activation of each pathway is controlled by two higher level "task-demand" nodes of each task. Depending on which task is activated, units within each pathway are biased via activation and inhibition connections between nodes. Switch costs within this model arise from ongoing activation and inhibition of uncued task pathways.

A few authors also used the integrative ACT-R framework to model switch costs. For instance, Sohn and Anderson (2001) proposed that activated "declarative chunks" configure the goal state of the agent. Within this framework, switch costs reflect competition in retrieving declarative chunks of the currently cued task, as well as the decay of activated chunks from the uncued task. Similarly, Altmann and Gray (2008) proposed that behavior is guided by task cues, or task codes that are retrieved from episodic memory. Within their model, task codes are active to varying degrees and switch costs arise from competition between activation levels of old, uncued task codes and new, cued task codes.

More recent modeling efforts have also focused on explaining how memory and attentional processes contribute to task-switching performance (e.g., Bridewell et al., 2018; Schmidt et al., 2020). A somewhat different approach was taken by Steyvers et al. (2019), who developed a model that provides a way of quantifying both effects of preparation and task-set inertia via activation weights, as opposed to postulating detailed memory- or attention-based cognitive dynamics that give rise to task-set reconfiguration. This model was applied to Lumosity data to capture age-related individual differences in and effects of extended training on switch costs and serves as the basis for the model used in the current work.

Flanker Lumosity Task

In standard versions of the Eriksen flanker task people are instructed to produce a designated response to a target that is flanked by response congruent or incongruent stimuli. The upper panel of Figure 2 shows the Lumosity version of the flanker task. On each trial, people are shown a configuration of birds and are instructed to respond to the pointing direction of the center bird as quickly and accurately as they can, while ignoring the pointing direction of the four flanking birds.

Cognitive control in the flanker task is typically quantified via the subtraction method, which involves taking the difference in RTs and/or accuracy between two conditions, such as a conflict neutral and incongruent conditions, or congruent and incongruent conditions. A common finding in this task is the presence of a congruency effect (lower panel of Figure 2), which is that RTs are faster and people make fewer errors when flanking stimuli potentiate the same response as the target than when they potentiate a different response. Variations in the magnitude of these congruency effects across individuals are typically interpreted as a measure of how well individuals prioritize response-relevant information (the target stimulus) and/or to inhibit response-irrelevant information (the flanking stimuli; e.g., Ong et al., 2017; Sanders et al., 2018; Schroeder et al., 2018).

Previous Theories and Models of Flanker Effects

Mainstream theories of performance in the flanker task postulate that it involves an effortful process of attentional selection. Consistent with this view, B. A. Eriksen and Eriksen (1974) found that flanker interference increased as the spatial distance between the target and flanker decreased. In later work, Gratton et al. (1988) found that the magnitude of congruency effects is larger at shorter RTs. A central goal of models of the flanker task has been to explain these spatial and temporal dynamics of selective attention. These flanker models are commonly formalized within a sequential sampling framework (Ratcliff et al., 2016), according to which processing evolves via an accumulation of information, until a decision threshold is reached and a response is selected and produced.

For instance, the shrinking spotlight model (White et al., 2011) postulates that initially both target and flanker stimuli contribute to the evidence accumulation process. However, over time, the proportion of attention distributed to the target increases, such that it receives priority in driving the decision process. This model is based on *spotlight* theories of attention, according to which attentional control is instantiated by directing and focusing an attentional spotlight on goal-relevant stimuli (C. W. Eriksen & St James, 1986).

Hübner et al. (2010) proposed a two-stage model in which both stages also involve evidence accumulation, but selection of stimuli occurs discretely rather than continuously. In the first stage, items in the display are perceptually filtered at an "early selection phase," until either a response is produced, or a single stimulus is selected. If a stimulus is selected in the first phase, evidence accumulation continues into a second stage, in which it is solely determined by the previously selected stimulus. This model is based on dual-stage models (Johnston & Heinz, 1978), that postulate a contribution of both early (e.g., Broadbent, 1958) and late (e.g., Deutsch & Deutsch, 1963) selection processes in the guidance of visual attention.

A more recent diffusion model for conflict tasks proposed by Ulrich et al. (2016), posits that evidence accumulation proceeds via an automatic and controlled pathway. The relative influence of automatic processes—which process flankers—varies over time, being most pronounced early on. In contrast, the controlled process is guided solely by the target and is constant over time. This modeling framework is based on mainstream models of cognitive control (e.g., Shiffrin & Schneider, 1977) that postulate a competition between automatic and controlled modes of processing. Importantly, each of these models was used to account for a wide range of phenomena in the flanker task, such as effects of target-flanker spatial distance and the temporal dynamics of congruency effects. Furthermore, like the current model, all of these models postulate that performance in the flanker task proceeds via an accumulation of evidence over time.

In addition to congruency effects, another major phenomenon in the flanker literature is the finding that flanker interference costs tend to diminish within a run of flanker incongruent trials (Gratton et al., 1992), sometimes referred to as sequential "adaptation" to conflict. Much of the literature on sequential effects in the flanker task focused on examining whether these effects reflect the role of executive processes that adapt to response conflict (e.g., Botvinick et al., 2001; Ullsperger et al., 2005), effects of associative priming (e.g., Mayr et al., 2003; Nieuwenhuis et al., 2006), or episodic learning (e.g., Schmidt & Weissman, 2016). To preview, in Appendix E we report a variant of the flanker model that captures sequential effects, although, as we discuss, we do not find that this version improves our ability to predict performance across tasks.

Domain-General and Domain-Specific Theories

To summarize, despite their different structures, the task-switching and flanker tasks are both theorized to measure people's ability to dynamically adapt their top–down settings to up-weight and/or down-weight goal-relevant information. Some evidence suggests that both the flanker and task-switching tasks may be related to individual differences in indices of global cognitive and neural function (e.g., Belleville et al., 2008; Pontifex et al., 2012; Roberts et al., 2010; Salthouse et al., 1998), and real-world outcomes such as academic performance (Unsworth et al., 2012) and attention failures (e.g., Cepeda et al., 2000; Pontifex et al., 2013; Unsworth et al., 2012). These findings serve as provisional evidence for the view that both tasks may probe a common, domain-general attentional control process (Cohen et al., 1990).

Moreover, in recent work Steyvers and Schafer (2020) used a data-driven latent modeling approach to examine covariation in performance across different Lumosity tasks as a function of training. Relevant in the current context, is that these authors found a high correlation in performance between these two tasks, which tied to a common latent factor related to executive attention. This work also provides provisional support for the view that both tasks probe a common cognitive control process.

Nevertheless, it is also possible that these tasks do not probe common cognitive control processes, but rely on multiple, independent control mechanisms that can operate in parallel (Egner, 2008). A conceptually similar proposal is that people develop specific tricks for solving different cognitive control problems (Logan, 2017). This view entails that cognitive

control processes are tethered to specific task demands, and that processes engaged by the two tasks are not tied to a more general ability to upregulate top–down control settings. Instead, prior evidence that both tasks predict other indices of cognitive function and are tied to a common latent factor, may reflect the fact that they are associated with a third variable, such as perceptual processing speed, or strategic differences in how people approach the tasks. As reviewed next, there is much theoretical and empirical work that suggests that mainstream measures of control processes could be confounded with these other sources of individual differences.

Challenges for Identifying Shared Control Processes Measurement With the Subtraction Method

On the surface, examining whether cognitive control processes are shared between the flanker and task-switching tasks may seem straightforward. For instance, researchers could use an individual difference approach and test for a presence of correlations in the size of congruency effects and task-switching costs, respectively. Related approaches involve coupling subtraction methods with more sophisticated covariance-based techniques, such as factor analysis (e.g., Keye et al., 2009; Redick et al., 2016; Treviño et al., 2021). Although these approaches may have intuitive appeal they do not provide a rigorous method for examining which processes are shared across tasks (see: Frischkorn & Schubert, 2018). This is because quantifying cognitive control via subtraction methods has several fundamental limitations, which, in principle, cannot permit researchers to infer that they are process-pure measures of control processes.

The first limitation of subtraction methods is that congruency effects and task-switching costs are captured separately for RTs and accuracy measures, which makes it difficult to capture strategies in speed and accuracy tradeoffs. This can profoundly compromise the interpretation of difference scores across individuals because much evidence suggests that people vary in how they strategically approach the task (see Draheim et al., 2019; Hedge et al., 2021; Hedge, Powell, Bompas, et al., 2018; Rey-Mermet et al., 2021). Although some metrics, such as the inverse efficiency scores (Townsend & Ashby, 1983), have been derived to jointly represent accuracy and RTs, their efficacy is debated (Liesefeld & Janczyk, 2019).

Second, accuracy scores lie on a bounded scale and, therefore, comparing the effect of interference effects on accuracy scores for individuals that have overall different levels of accuracy is deeply problematic (e.g., Loftus, 1978). As an extreme example of this issue, consider two people who show the same-sized congruency effect on the flanker task, such that Person 1 has 60% correct responses on congruent and 50% correct response on incongruent trials, whereas Person 2 has 100% correct responses on congruent and 90% correct responses on incongruent trials. The raw difference in accuracy between congruent and incongruent conditions is the same for these two people (10%), however, because accuracy lies on a bounded scale (Loftus, 1978) and is a nonlinear measure of performance (Swets, 1986) these difference scores may not be (and likely are not) comparable.

Finally, the first two limitations highlight the fundamental short-coming of the subtraction method, which is that it may fail to delineate processes that reflect cognitive control from other "lower level" processes. That is, without rigorous tools for quantifying and

separating cognitive control processes from other processes, such as perceptual processing speed (Schubert et al., 2018) or control over speed and accuracy tradeoffs[2] (Burgoyne & Engle, 2020), it follows that researchers cannot conclude that these metrics yield process pure measures of cognitive control (Frischkorn & Schubert, 2018). Accordingly, the finding that there is an association between congruency effects and task-switching costs cannot be used to infer what processes are shared across tasks (Hedge et al., 2021).

Homogeneous and Small Samples

Another practical challenge for modeling invariants across tasks is obtaining sufficiently heterogeneous and large sample sizes, such that individual differences in performance on different tasks are detectable (e.g., Cronbach & Furby, 1970). This is especially relevant for modeling individual differences across tasks that yield robust effects across individuals, such as the flanker and task-switching tasks because tasks that yield robust effects across individuals may also yield decreased between-individual variance (Hedge, Powell, & Sumner, 2018). Therefore, in order to capture individual differences across tasks, researchers must obtain sufficiently heterogeneous samples, as well as a sufficient number of observations per person to obtain reliable estimates of performance for each individual (Rouder et al., 2019). This criterion is often difficult to meet in typical laboratory studies, where samples tend to be relatively small (less than 100 observations per cell within a person) and homogeneous (undergraduate university students).

Addressing Prior Limitations: Applying Computational Models to a Large-Scale Sample

One way of addressing the limitations summarized above is to use computational models of cognition that quantitatively delineate latent constructs via model parameters. Accordingly, researchers may examine whether parameters that capture cognitive control processes on one task can be used to predict performance on a different task (e.g., Hedge et al., 2021; Rey-Mermet et al., 2021; Turner et al., 2019; Ulrich et al., 2016). This is the approach taken here. Specifically, we fit computational models to data from each task. We then use a formal linking approach by examining whether swapping parameters across the two task models permits us to make predictions of individual differences in performance on each of the tasks.

We also apply our modeling and analysis to a large scale Lumosity sample, which is highly diverse and large at the levels of individuals and trials. Especially relevant to modeling individual differences in cognitive control (e.g., Campbell et al., 2012), our sample consists of approximately 500 users who vary in age from at least 21 years of age to at most 80 years of age. On average these individuals trained on the two tasks over the course of years, yielding an average of over a thousand trials in each task per person. To summarize, by leveraging computational models and data from a large scale sample, our work attempts to resolve the fundamental limitations of subtraction methods used in prior work. In the following section, we explain how our computational models separate cognitive control processes from other processes in the two tasks.

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[2]For convenience, throughout the article we refer to perceptual/motor speed and strategies in speed and accuracy tradeoffs as lower-level processing dynamics, to distinguish them from higher-level attention control.

Computational Models of the Task-Switching and Flanker Lumosity Tasks

Within our modeling framework, a primary distinction[3] is between a cognitive control versus a perceptual/motor model of each task. As we discuss later, these model variants allow us to decouple attentional control processes from speed and accuracy strategies and perceptual processing and motor response speed. In the following sections, we describe the full cognitive control models of each task, and then the reduced perceptual/motor variants.

Fundamental to our cognitive control task-switching and flanker models is that they combine parameters in standard accumulator models[4] with *activation weights.* Activation weights are parameters that capture people's ability to engage cognitive control processes in order to prioritize task-relevant information of the current task or deprioritize task-irrelevant information of the current task, or some combination of the two.

In addition to separating cognitive control from other processes, an advantage of modeling control dynamics via activation weights is that our models are agnostic regarding what specific memory and/or attention processes are engaged, and how they are engaged when people exert acts of cognitive control. Our task models simply posit that there are graded levels of cognitive control, which can be captured by the degree to which task-relevant and/or task-irrelevant information is activated in the cognitive system. Thus, the current models are treated as measurement models that are largely compatible with different cognitive architectures and neural theories regarding precisely how cognitive control is instantiated in these tasks.

Figure 3 shows example displays from the flanker and task-switching tasks (Panel A) and a schematic representation of the cognitive control flanker and task-switching models (Panel B), which depicts how cognitive control activation weights determine performance on each trial of each task. Within each model, activation weights combine multiplicatively with perceptual input features, to yield a measure of weighted featural encoding. The sum of the weighted features across stimulus dimensions form the drift rates in the accumulator models.

Perceptual encoding parameters represent what we for convenience refer to as "low-level" processes, namely, the efficiency with which people process a physical stimulus. The task activation weights quantify people's ability to selectively process information within each experimental condition. Finally, the product of these parameters, that is, the multiplicatively weighted featural encoding represents the top–down regulation of lower level perceptual processes. In the next sections, we describe how cognitive control activation weights are used in the task-switching and flanker models.

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[3]A secondary distinction is between *Baseline* cognitive control model variants that do not capture a change in cognitive control as a function of learning, and *Learning* cognitive control models that do capture changes in cognitive control as a function of learning. As noted, for ease of exposition we focus on the Baseline cognitive control models in the main text (which we simply refer to as Cognitive control models), and discuss the Learning model extensions in Appendix D.
[4]We note here that previous work on conflict tasks focused on single accumulator models with two boundaries to model two choice situations (e.g., White et al., 2011) and our work focuses on multiple racing accumulators, one for each response.

Cognitive Control Model of the Task-Switching Task

The task-switching cognitive control model postulates that cognitive control may operate in two ways, namely, through the prioritization of the cued task (pointing task in Figure 3), or deprioritization of the uncued task (movement task in Figure 3), or some combination of these processes. The degree to which people prioritize task-relevant features and/or deprioritize task-irrelevant features may change as a function of the number of consecutive trials spent on a single task.

More precisely, when individuals complete a series of trials on the same task, they may improve in up-weighting features relevant to that task and/or inhibiting features not relevant to that task. These changes in cognitive control dynamics as a function of short-term practice underpins the improvement in performance in RTs and accuracy that is typically observed in task-switching tasks (Figure 1). Within the task-switching model, the two changes in activation as a function of trial run are captured by the following two equations:

$$A_{k,i} = B_{k-1} + (\tau - B_{k-1}) \times (1 - e^{-i\delta_\tau}).$$ (1)

$$B_{k,i} = A_{k-1} + (\gamma - A_{k-1}) \times (1 - e^{-i\delta_\gamma}).$$ (2)

In the above equations, values of $A_{k,i}$ and $B_{k,i}$ are activation weights for the cued and uncued task, respectively. In Equation 1, the activation level of the cued task ($A_{k,i}$) on a given trial i within a run of trials k, starts at a baseline level of activation (B_{k-1}), which was achieved on the previous run of trials ($k - 1$), when the currently cued task was the uncued task.

As shown in Figure 4 activation of the cued task can increase with each trial toward an asymptotic level of activation, which is captured with parameter τ. Within the model, the cued task increases towards asymptote at an exponential rate, which is captured by parameter δ_τ. Similarly, in Equation 2, the activation of the currently uncued task on a given trial ($B_{k,i}$) starts at an asymptotic level of activation, which was achieved in the previous run of trials (A_{k-1}), and decreases toward a baseline level of activation, which is captured by parameter γ. This change in activation also follows an exponential growth function and is captured by rate parameter δ_γ.

The product of activation weights and perceptual input for displayed stimulus features (ξ_D) yields a measure of weighted featural encoding (b). More precisely, the weighted features of the cued task (b_{Cued}) (moving task in Figure 3) are given by the product $b_{Cued} = A \times \xi_D$, where A quantifies levels of activation of the cued task on a given trial i within a run of trials k (k and i subscripts are omitted from the equations for simplicity). Similarly, the weighted features of the uncued task (b_{Uncued}) (pointing task in Figure 3) are given by the product $b_{Uncued} = B \times \xi_D$, where B captures levels of inhibition of the uncued task on a given trial i within run of trials k. This separation between the unweighted perceptual encoding and weighted cued and uncued task features, formalizes the theoretical distinction between processes that reflect the

speed of perceptual evidence accumulation and cognitive control processes engaged in the task-switching task, respectively.

The weighted featural encoding is summed across stimuli dimensions to form drift rates (c) in a multialternative racing diffusion model (for review see Ratcliff et al., 2016). The accumulator that first crosses a response threshold wins the race and determines the response and response time. The accumulator model also has parameters α, σ and T_{er}, which denote the response threshold, within-trial variance of the drift rates, and nondecision (e.g., motor response) time, respectively. Finally, we also make the assumption that on some trials people may erroneously produce responses that are not associated with a displayed feature dimension (e.g., left or right in Figure 3); these responses are modeled by allowing a residual activation of nondisplayed perceptual features captured by parameter ξ_N.

Together, facilitation and interference in these models are produced by summing measures of weighted featural encoding across stimulus dimensions. For instance, on congruent trials the activation of the cued task feature (e.g., pointing up) is combined with a partially activated uncued task feature (e.g., moving up) resulting in a higher value of summed featural encoding (e.g., for "Up") and corresponding drift rate for the correct response. On incongruent trials, the perceptual encoding across different features (e.g., pointing up and moving down) distributes the activation across different response dimensions, resulting in a relatively decreased drift rate for the correct response and an increased drift rate for the incorrect response.

Cognitive Control Model of the Flanker Task

For the purpose of our linking analysis, we developed a novel model of the flanker task that is mathematically similar to the task-switching model. Like the cognitive control task-switching model, the cognitive control flanker model postulates that on each trial cognitive control processes reflect people's ability to prioritize features that are relevant to the task-defined goals (the target) and deprioritize features that may be irrelevant to the task-defined goals (flankers). The major difference between the two models is that cognitive control activation functions in the flanker model capture the degree to which individuals weight target or flankers, rather than features of a cued or uncued task.

Another difference between the two models is that the flanker model does not posit that activation weights change as a function of trial run. We did not model changes in activation weights as a function of trial run because we found that this "sequential effects" variant of the flanker model does worse at predicting performance on the task-switching task (see Appendix E, for results and discussion). Thus, the two activation functions for the target and flankers are captured simply with parameters τ and γ, respectively.

Like in the task-switching model, activation weights for target and flankers combine multiplicatively with perceptual encoding ($\tau \times \xi_D$ and $\gamma \times \xi_D$, respectively) to yield a measure of weighted featural encoding of the target and flankers (b_T and b_F, respectively). The sum of the features across the same response dimensions determines the accumulation of evidence for each response. For instance, on incongruent trials, the activation of the target feature

(b_T) competes with the partially activated flanker features (b_F). Thus, interference is modeled as a reduction in drift rate, produced by summing task-relevant and -irrelevant features for different responses. On congruent trials the target (b_T) and flanker (b_F) features are summed across the same response leading to an increase in drift rate for the task-relevant response. The cognitive control flanker model also includes parameters ξ_N, α, σ and T_{er}, which capture the drift rate for nondisplayed features, the response threshold, within-trial variance of the drift rates, and nondecision (e.g., motor response) time, respectively.

Perceptual/motor Model of the Task-Switching and Flanker Tasks

In this section, we elaborate on how our models permit us to dissociate low-level perceptual and motor processes, as well as speed and accuracy strategies, from high-level cognitive control processes. In particular, we do this by comparing performance of the cognitive control task models to a reduced version of these models, which does not capture cognitive control dynamics. We refer to this reduced model variant as the perceptual/motor model because it postulates that processing in both cognitive control tasks is driven solely by lower level processing dynamics, such as speed and accuracy tradeoffs and the speed with which people process stimuli in the external environment. More precisely, the perceptual/motor model is simply a standard multiresponse accumulator model (Donkin & Brown, 2018). A schematic of this model is shown in Figure 3 Panel C.

The core difference between the perceptual/motor and cognitive control model is that within the perceptual/motor model processing in both tasks is determined by the rate at which people accrue information about stimuli in the external environment in the absence of cognitive control processes. In particular, we assume that on each trial an external stimulus is perceived, and that speed of responding is determined by the rate at which perceptual evidence accrues, passes a response threshold, and motor responses are enacted in the absence of top–down regulation.

For instance, in the example displays in Figure 3 Panel A, stimuli in both the flanker and task-switching tasks potentiate the up and down response. The rate of perceptual evidence accumulation for these two displayed features is captured with a single parameter ξ_D, that is, the perceptual encoding parameter for displayed features. The winning response would be determined simply by the outcome of stochastically varying (Wiener) processes with perceptual encoding parameters ξ_D for displayed features and ξ_N for nondisplayed features, with no weighting from top–down activation weights.

Finally, the perceptual/motor model also includes parameters α, σ and T_{er}, which denote the response threshold, within-trial variance of the drift rates, and nondecision time, respectively. The response threshold parameter α captures how much evidence is accrued prior to response execution, and quantifies speed and accuracy tradeoff strategies. The nondecision parameter T_{er} quantifies processes that are not engaged during response selection, such as motor execution time. In our primary analysis, we examine whether cognitive control processes versus solely lower level processes are shared across the two tasks by comparing predictive accuracy between the full cognitive control and reduced perceptual/motor model of each task.

Validating Cognitive Control Model Assumptions

A fundamental assumption of our analysis is that activation weights in each of the cognitive control models selectively capture cognitive control processes as opposed to other task-strategies, such as speed and accuracy tradeoffs, or perceptual speed accrual. This assumption is based on the mathematical form of our accumulator models and their relation to the task structures, as well as prior work by Steyvers et al. (2019) that used the task-switching model to predict age-related differences in cognitive control. Here, we take another step toward validating this assumption with simulations. Our simulations are based on recent work of Hedge et al. (2021), who found that variation in noncognitive control parameters in Ulrich et al.s' (2016) diffusion model can produce response conflict like effects at the level of RTs and accuracy, even when cognitive control parameters in the model were held constant. The goal of our parameter recovery analysis was to directly examine whether non-cognitive control parameters can mimic effects of cognitive control parameters in our models.

To this end, we assessed our ability to recover each parameter while systematically varying other parameters in the model. The logic behind this analysis is that if only cognitive control parameters capture control processes, we should be able to reliably recover each value of the cognitive control parameters even when other parameters in the model vary. Conversely, if varying noncognitive control (e.g., response thresholds) parameters produces conflict like flanker or task-switching costs, we should be unable to reliably recover the true-data generating values of the cognitive control parameters if we simultaneously vary other (e.g., response threshold) parameters in the model. These parameter recovery simulations and results are described in detail in Appendix A.

To summarize, we find that we can reliably recover all parameters in our model, even when other parameters in the model were systematically varied. Therefore, we find strong convergent support for our assumption that, within our modeling framework, cognitive control parameters in our models selectively capture cognitive control processes, as opposed to nuisance task-strategies or perceptual information processing speed.

Intended Scope of Current Models

The models we use could be enhanced to capture a wide range of phenomena, however, we do not attempt to model every phenomenon reported in these tasks. That is, our goal is not to find a model that best fits the data in each of the tasks, or to provide detailed process-level description of these effects. Therefore, we gloss over modeling certain processing dynamics that capture how attentional control processes may be instantiated in each of the tasks.

For instance, our task-switching model does not formally capture *how* task-set preparation or inertia leads to task switch costs. Likewise, we do not attempt to model the temporal dynamics of congruency effects, such as the common observation that errors are faster than correct responses (Gratton et al., 1988). Instead, the model has the potential to capture the contribution of both processes via baseline and asymptotic activation weights. Likewise, our flanker model is agnostic with respect to whether attention is allocated to the target stimulus continuously or discretely (e.g., Hübner & Töbel, 2012).

In our view, such simplifying assumptions are desirable as a first-step toward linking models of different tasks. This is because effective generalization requires some simplification and abstraction away from detailed descriptions of processes within specific tasks. Likewise, it can be conceptually and practically challenging to map parameters across detailed process-level models of structurally different tasks. For this reason, we worked with models that have a similar functional form and focused on quantifying individual differences in levels of attentional control in the two tasks via activation weights. These models can be viewed as measurement models, which aligns with the use of simpler measurement models in other recent-linking approaches (e.g., Cox et al., 2018).

Linking Models via Parameter Substitution

We test the prediction that cognitive control processes are shared across tasks by examining whether parameters from one task model generalize to another task model. As previewed in our example with Bill and Sue, we implement this in a primary and secondary analysis by comparing predictive accuracy for different ways of substituting parameters across individuals and task models.

Primary Analysis

Our primary analysis has two levels. On one level, we evaluate our ability to predict individual differences across task models by substituting parameters in different ways across individuals. On the second level, we directly test whether including cognitive control parameters in our task models increases our capacity to predict individual differences in performance. This model comparison provides a strong test of whether cognitive control process are shared across the two tasks. We describe each of these analyses, as well as our top–down approach toward substitution next.

Unpermuted Versus Permuted Substitution—Our analysis is based on an individual differences approach because we compare predictive accuracy when we use the same person's parameters from the source task model to predict their data on the target task (unpermuted analysis), versus when we use a different person's parameters (permuted analysis). For instance, as shown in Panels A and B of Figure 5, in the unpermuted case we substitute Bill's and Sue's best-fitting parameters from the source (e.g., flanker) task, into the target (task-switching) task model to predict Bill's and Sue's behavior on the target task, respectively. We compare this prediction to the situation in which we permute parameters across individuals, and instead use Bill's and Sue's parameters from the source model to predict Sue's and Bill's behavior on the target task, respectively. In the general case with more than two individuals, we pseudorandomly permute parameters across individuals, with the constraint that the same person's parameters from the source model are not used to predict their data on the target task.

If model parameters capture individual differences in the data and if they can be used to predict performance across tasks, predictive accuracy should be higher when we preserve the identity of individuals across tasks and do not permute parameters across individuals. We note that this is a conservative test for individual differences, which hinges on the assumption that there is sufficient heterogeneity in the data to detect individual differences.

Substitution Across Perceptual/motor Versus Cognitive Control Models—One limitation of substituting parameters across the same variant of each task model, is that this does not tell us which parameters increase predictive accuracy. For instance, if we find that unpermuted substitution increases predictive accuracy relative to permuted substitution this would indicate that some processes are shared across tasks, however, it would not tell us whether cognitive control processes are shared across tasks, or only other variables, such as perceptual processing speed. One way to address this question, is to consider different variants of each task model. In particular, to directly test whether cognitive control processes are shared across tasks, we can compare predictive accuracy of the full cognitive control variants of these models, which include cognitive control parameters, with reduced perceptual/motor versions of these models, which do not include cognitive control parameters.

This model comparison is depicted in Panels A and B of Figure 5, which shows unpermuted and permuted substitution using the cognitive control and perceptual/motor model, respectively. For instance, if we find that unpermuted substitution in the cognitive control model does not increase predictive accuracy relative to unpermuted substitution within the perceptual/motor model, this would provide very strong evidence for the view that all that is shared between the two tasks are "low-level" variables such as information processing speed and strategic differences in speed and accuracy tradeoffs. Conceptually, this result would entail that knowing an individual's performance on one of the cognitive control tasks (e.g., flanker), does not provide information over-and-above knowing how that person performs in tasks that require simple responding without top–down, attentional modulation. Conversely, if we find that unpermuted substitution within cognitive control versions of each task model increases predictive accuracy over-and-above permuted substitution, as well as unpermuted substitution within the perceptual/motor task models, this would provide evidence that the two tasks engage common cognitive control processes.

Top–Down Approach Toward Substitution—We use a top–down approach to substitute parameters between models, meaning that we guide our substitution analysis with a priori predictions regarding which model parameters should be substituted across models. This contrasts to a greedy approach with which we would guide parameter substitution across models based on substitutions that increase predictive accuracy. Neither approach is guaranteed to increase predictive accuracy in our comparisons, but the top–down approach is more conservative and principled because it has fewer degrees of freedom and is theoretically constrained.

The top–down approach is represented for a subset of parameters in Figure 5. For instance, in the cognitive control model we reasoned that parameter τ, which captures prioritization of the target in the flanker task should be substituted in for the parameter τ, which captures prioritization of task-relevant features (of the cued task) in the task-switching model. Similarly, we reasoned that parameter γ, which captures inhibition of flankers in the flanker model should be substituted in for parameter γ, which captures inhibition of task-irrelevant features (of the uncued task) in the task-switching model. Other parameters

in the accumulator model also have a direct mapping between each model. For instance, perceptual/motor models have drift rates ξ that capture the efficiency with which individuals process stimuli in the external environment and we directly substituted these parameters across models of the two tasks.

Secondary Analysis

The goal of our secondary analysis is to complement our primary analysis in the situation that we find that the cognitive control model outperforms the perceptual/motor model. That, is our primary analysis directly addresses whether cognitive control parameters in each model help improve across-task prediction. If we found that the perceptual/motor task models predict data as well as the cognitive control task models, this would provide very strong evidence for the view that there are no shared control processes across the two tasks. However, if the cognitive control model outperforms the perceptual/motor model in prediction, this could reflect the fact that perceptual/motor model fails to capture general trends in the task data that are common to all individuals.[5] In other words, we cannot determine definitively whether superior performance of the cognitive control over the perceptual/motor model reflects the fact that cognitive control processes are not shared across tasks, or the fact that the perceptual/motor model is misspecified for these tasks.

Comparison of Unpermuted and Mixed Substitution in the Cognitive Control Model—As a complementary test of our ability to predict individual differences in cognitive control, we implement a secondary analysis, which is shown in Panel C of Figure 5 and which we refer to as the *mixed substitution analysis.* For this analysis, we use the full cognitive control model, however, we make across task predictions by substituting all low-level parameters from the same individual (unpermuted subset), and all attentional control parameters from a different individual (permuted subset). We compare predictive accuracy for this substitution with the scenario where we substitute all parameters into the cognitive control model from the same individual. With these substitution schemes, we can directly test whether cognitive control parameters from the same person (shown in the top row of Panel A) improve predictive accuracy over-and-above cognitive control parameters from a different person (shown in Panel C). This comparison is a complementary test of whether there are shared cognitive control processes in the two tasks.

Applying Models to Lumosity Data

In the following sections, we describe our large scale Lumosity sample. A major strength of using a Lumosity sample is that it is large at the level of individual users and trials. Our sample is also heterogeneous in age, which increases our ability to detect individual differences in cognitive control. Finally, users complete the tasks voluntarily and are therefore likely intrinsically motivated to perform each of the tasks. After describing our Lumosity sample, we present technical details of our analysis and modeling. We then report results of our primary and secondary parameter substitution analyses. These analyses provide insight into our main question of whether cognitive control processes are shared

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[5]For instance, since the model does not include attentional weights, it predicts that, overall, people should respond equiprobably tow the target and flankers and be approximately 50% accurate on response incongruent trials.

across tasks. In Appendix D, we consider extensions of the cognitive control task models, which capture how cognitive control processes change as a function of learning.

Characteristics of the Sample

This research is exempt from review by the institutional review board because we are analyzing historical data and did not design the studies ourselves. We used a sample of data from 500 users who trained on "Ebb and Flow," a task-switching game on the Lumosity platform, and "Lost in Migration" a flanker game on the Lumosity platform. From this set, we selected all users who completed at least 60 game sessions of the task-switching and flanker tasks. This left 495 users for analysis. Most of the users in our sample identified as female (66%), others identified as male (29%), and the remaining users (5%) did not report their gender. These users varied in age from 21 to 80 years old, with a mean age of 58 years ($SD = 12$ years). Users reported being in one of the following eight education categories (percentages are rounded to the nearest integer): some high school (3%), high school (11%), some college (18%), associates degree (31%), bachelor's degree (6%), professional degree (17%), master's degree (3%), and PhD (5%). All users listed English as their preferred language.

This sample of users trained on each task up to 2 years. Each game session has approximately 60 trials and each person completed approximately 3,600 trials of each task. We conditioned the first analysis on data from the 30 to 60th game session. We did this because previous work indicates that performance tends to asymptote within this range of training (Steyvers & Schafer, 2020), and our first goal was to model cognitive control processes, rather a change in cognitive control processes as a function of training.

Technical Details of Model Fitting

Our model fitting approach is adapted from Steyvers et al. (2019). Both the task-switching and flanker model are built on top of four-response alternative racing accumulator models, which determine the joint distribution over RTs and response choices. The likelihood function for the model is given by the expression $g_k(t) = f_k(t) \prod_{j \neq k} (1 - F_j(t))$ (Heathcote & Love, 2012; Steyvers et al., 2019). In this equation, $g_k(t)$ denotes the probability density function for response k at time t, which is expressed in terms of the probability density function of accumulator k ($f_k(t)$) and cumulative density functions of the remaining accumulators $F_j(t)$). This expression captures the probability that accumulator k reaches the response threshold before the remaining accumulators j. As described in the main text, previous work on conflict tasks focused on single accumulator models with two boundaries to model two choice situations and our work focuses on multiple racing accumulators, one for each response.

In the cognitive control variant of the task models, perceptual-encoding parameters for displayed stimulus dimensions are weighted by activation weights to capture effects of top–down attentional control. In the perceptual/motor model, perceptual-encoding parameters are not weighted by activation weights and capture simply the speed of perceptual information accrual. All models include a separate perceptual-encoding parameter for stimuli that are not

shown on a given trial, a response threshold, a parameter that captures within-trial variance of the drift rates and a nondecision time parameter.

We fit the task-switching and flanker model using Bayesian estimation. Model parameters were estimated separately for each user. In addition, the model was estimated at the level of individual trials; no aggregation was applied to combine trials into different conditions before model estimation. The posterior distribution was estimated using an inference procedure called differential evolution Markov chain Monte Calro (DE-MCMC; Ter Braak, 2006). DE-MCMC combines a genetic algorithm with MCMC, such that multiple chains are run in parallel and new parameter proposals are made using the difference between chains. This variant of MCMC has been shown to increase convergence efficiency and is more robust when there are correlations between parameters (Turner, Sederberg, et al., 2013).

DE-MCMC was applied separately to data from each task and each individual with 30 chains and 500 iterations. Parameters from each model were taken from the last sample of each chain. Code was adapted from Steyvers et al. (2019) and implemented in Matlab. Data and model fitting code are available through the Open Science Framework Repository at the following link: https://osf.io/6hjwv/. We used cloud computing resources from Amazon's elastic computing cloud to increase computing efficiency.

Evaluating Predictive Accuracy of Models Within Tasks

We evaluated the predictive accuracy of our models within each of the tasks to ensure that they capture key trends in the data. For this analysis, we applied five-fold cross-validation to measure the predictive accuracy of each model within tasks, and quantified predictive accuracy at different levels of analysis, separately for reaction times and accuracy. For ease of exposition, we report technical details and results of this analysis in Appendix B. To summarize, we found that cognitive control task both models capture key quantitative and qualitative trends in the data.

Technical Details of Parameter Substitution

For the primary and secondary parameter substitution analyses we used entire samples of data from each task to fit task-models and estimate best-fitting parameters. This ensured that we had sufficient power to make fine grained across-task predictions at the level of individual users. For the unpermuted analysis, we obtained best-fitting parameters for each individual and each of the 30 chains, and then substituted these parameter values into the equation of the target task model to generate model predictions. We then averaged these model predictions across the 30 chains to estimate the same individual's data on the target task. The permuted analysis was identical, except we permuted parameters across individuals, such that we used one individual's best-fitting parameters from the source task to predict a different individual's data on the target task. For the permuted analysis, we repeated the permutation analysis 100 times with different permutations of individuals.

We measure predictive accuracy with the predictive log-likelihood (PLL) because it jointly captures the discrepancy between all of the observed and predicted (response and RT) data in the target task. To emphasize, the PLL quantifies predictive accuracy on an unseen, novel

task, not the goodness of fit of the models to data. For the permuted analysis, we report the PLL aggregated across 100 permutations.

Results of Parameter Substitution Analyses

Figure 6 shows individual subject RT and accuracy data from four randomly drawn users for each of the two tasks. In addition, the figure shows model fits of the target model. We also show outcome of two across-task predictions. For simplicity, we focus on across-task predictions with the full cognitive control models with unpermuted and permuted parameters across individuals (Panel A of Figure 5). As shown for these sample users, in general we find that parameter substitution across cognitive control models within the same person (unpermuted analysis) captures trends in individual data better than when parameters are mixed across people (permuted analysis).

The main results of prediction from all substitution and model comparisons are shown in Figure 7. Critically, we found that unpermuted substitution with the cognitive control model improves predictive accuracy of individual differences in performance on both tasks. In our primary analysis, statistical comparisons reveal that the perceptual/motor and cognitive control models both capture individual differences in the data, and that the cognitive control model increases predictive accuracy relative to the perceptual/motor model. Likewise in our secondary analysis, we found that unpermuted substitution with the full cognitive control task models outperformed mixed parameter substitution with the cognitive control task models. In short, the results are consistent with the view that the flanker and task-switching tasks probe common latent cognitive control processes.

In the following sections, we report statistical comparisons for each target model for the primary and secondary analyses. To demonstrate that our results are robust across different statistical tests, we report a paired *t* test and a Wilcoxon-sign test (for simplicity, we report the absolute value of these statistics and discuss the directionality of the difference), as we all as the percentage of participants for which the reported outcome was obtained.

Target Task: Task-Switching

Primary Analysis.: We test the difference in PLL for both perceptual/motor and cognitive control[6] variants of the target model when parameters are permuted versus unpermuted.

There was a significant difference in the PLL of the perceptual/motor model with permuted and unpermuted parameters, $t(494) = 16.1$, $p < .0001$; $z = 14.5$, $p < .0001$; 79% of sample; favoring the target model with unpermuted ($\bar{X} = -1013$, Standard Error of the Mean [SEM] $= 33$) versus permuted ($\bar{X} = -1860$, SEM $= 47$) parameters. Similarly, there was significant difference in the PLL of the cognitive control model with permuted and unpermuted parameters, $t(494) = 33.48$, $p < .0001$; $z = 18.5$, $p < .0001$; 97% of sample; favoring the cognitive control model with unpermuted ($\bar{X} = -53$, SEM $= 41$) versus permuted

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[6]There are two parameters that could not be substituted from the Flanker model. Specifically, only the task-switching model quantifies sequential effects with rate parameters, whereas in the Flanker model activation weights are constant as a function of trial run. Therefore, when predicting performance on the task-switching task with both permuted and unpermuted substitution, we randomly sampled these rate parameters from a different individual and substituted them into the task-switching model.

parameters ($\bar{X} = -1397$, SEM = 49). These results indicate that both the perceptual/motor and cognitive control models captured individual differences in the data. For illustration, we show an alternative way of visualizing predictive accuracy with unpermuted and permuted substitutions with the full cognitive control model in Appendix C.

We also found that the cognitive control model yielded a large PLL than the perceptual/motor model both when parameters were permuted, $t(494) = 8.4$, $p < .0001$; $z = 7.22$, $p < .0001$; 60% of sample, and unpermuted, $t(494) = 18.98$, p .0001; $z = 16.43$, p .0001; 88% of sample. This suggests that cognitive control parameters in the task model capture additional shared variance across tasks. The fact that the cognitive control model outperforms the perceptual/motor model is not guaranteed. For comparison, we calculated a lower bound for the PLL if the cognitive control model fails to capture individual differences as well as aggregate level performance on each task, which was −8,694. This lower bound corresponds to the log-likelihood for the prior predictive, when the target task model is assessed for each individual by sampling parameters from a diffuse prior without any fitting to the observed data.

Finally, we tested the difference in the likelihood ratio separately for the perceptual/motor and cognitive control model when parameters were permuted and unpermuted (the likelihood ratio is simply the difference in PLL for each of the two models when the data are unpermuted vs. permuted). This test revealed that the likelihood ratio was higher, $t(494) = 8.6$, $p < .0001$; $z = 9.18$, $p < .0001$; 70% of sample, for the cognitive control model when data were unpermuted ($\bar{X} = 960$) versus permuted ($\bar{X} = 463$). Together, we find that the cognitive control target model increases predictive accuracy over and above the perceptual/motor target model and captures individual differences in the data.

Secondary Analysis.: For the secondary analysis, we compare predictive accuracy for this mixed substitution analysis to the unpermuted analysis with full cognitive control model. This comparison revealed that PLL was larger for the unpermuted than the mixed substitution ($\bar{X} = -419$, SEM = 33) analysis, $t(494) = 12.92$, $p < .0001$; $z = 13.98$, $p < .0001$; 83% of sample. Once again, these results provide converging support for the view that the two tasks engage common cognitive control processes.

For completion and to ensure that our results are consistent across different ways of analyzing the data, we also consider another variant of the mixed parameter substitution analysis in which attentional weights are substituted from a different task and the same person (unpermuted subset) and the remaining parameters are substituted from a different task and a different person (permuted subset). We compare this substitution to one where we substitute all parameters from a different task and person (permuted analysis), to examine whether substituting attentional weights from a different task and same person increases predictive accuracy. Consistent with this prediction, we find that PLL is higher when with this version of the mixed substitution ($\bar{X} = -954$, SEM = 62) than the permuted analysis, $t(494) = 4.58$, $p < .0001$; $z = 4.95$, $p < .0001$; 62% of sample.

Target Task: Flanker

<u>Primary Analysis.:</u> There was a significant difference in the PLL of the perceptual/motor model with permuted and unpermuted parameters, $t(494) = 7.76$, $p < .0001$; $z = 7.67$, $p < .0001$; 65.6% of sample; favoring the target model with unpermuted ($\bar{X} = -1960$, SEM $= 76$) versus permuted ($\bar{X} = -2473$, SEM $= 94$) parameters. Similarly there was significant difference in the PLL of the cognitive control model with permuted and unpermuted parameters, $t(494) = 21.35$, $p < .0001$; $z = 18.31$, $p < .0001$; 94% of sample; favoring the Cognitive control model with unpermuted ($\bar{X} = 205$, SEM $= 34$) versus permuted parameters ($\bar{X} = -1114$, SEM $= 59$). These results indicate that both the Perceptual/motor and Cognitive control models captured individual differences in the data. Again, for illustration, we show an alternative way of visualizing predictive accuracy with unpermuted and permuted substitutions with the full cognitive control model in Appendix C.

We also found that the cognitive control model yielded a large PLL than the perceptual/ motor model both when parameters were permuted, $t(494) = 23.3$, $p < .0001$; $z = 16.47$, $p < .0001$; 83% of sample, and unpermuted, $t(494) = 28.47$, $p < .0001$; $z = 19.22$, $p < .0001$; 99% of sample. Again, this reveals that cognitive control parameters in the task models increase predictive accuracy. Once again, for comparison, we calculated a lower bound for the PLL if the cognitive control model fails to capture individual differences as well as aggregate level performance on each task. This lower bound was –7,549.

For the critical comparison, we tested the difference in the likelihood ratio of the PLL between the perceptual/motor and cognitive control model when parameters were permuted versus unpermuted. This test revealed that the likelihood ratio was higher, $t(494) = 16.33$, $p < .0001$; $z = 14.16$, $p < .0001$; 80% of sample; indicating more support for the cognitive control model when data were unpermuted ($\bar{X} = 2165$) versus permuted ($\bar{X} = 1359$). Together, as before, we find that cognitive control parameters increase predictive accuracy of the target model and capture individual differences in the data.

<u>Secondary Analysis.:</u> A comparison between mixed and unpermuted substitution with the cognitive control model, revealed that PLL was larger for the unpermuted than the mixed substitution ($\bar{X} = -712$, SEM $= 49$) analysis, $t(494) = 19.87$, $p < .0001$; $z = 18.08$, $p < .0001$; 93% of sample. Again, these results provide converging support for the view that the two tasks engage common cognitive control processes.

Finally, we compare the mixed parameter substitution analysis in which attentional weights are substituted from a different task and the same person (unpermuted subset) and the remaining parameters are substituted from a different task and a different person (permuted subset) to one where we substitute all parameters from a different task and person (permuted analysis). Again, we find that PLL is higher when with this version of the mixed substitution ($\bar{X} = -582$, SEM $= 37$) than the permuted analysis, $t(494) = 26.41$, $p < .0001$; $z = 18.33$, $p < .0001$; 94% of sample.

Summary of Results

Our results reveal that parameters that capture cognitive control processes on one cognitive control task can be used to predict individual differences in performance on a different cognitive control task. We also find that we can predict individual differences across tasks with a model that captures changes in cognitive control dynamics as a function of learning. Collectively, these results indicate that performance on these two tasks may rely on a common higher level process that determines people's ability to effectively select goal-relevant information, as well as the change in cognitive control dynamics as a function of learning.

General Discussion

The finding that we predict individual differences in performance by swapping cognitive control parameters across models of different control tasks, provides provisional support for a domain-general view of cognitive control. These results may guide theoretical work that examines individual differences in cognitive control in clinical populations (e.g., Grahek et al., 2019; Hallion et al., 2017; Koster et al., 2017; McTeague et al., 2017), as well as whether cognitive control is an ability that could be trained (e.g., Edwards et al., 2018; Sala et al., 2019; Souders et al., 2017). For instance, our finding that structurally different laboratory tasks may probe common cognitive control processes, as well as how these processes change as a function of learning, is compatible with the view that extensive training on these tasks could improve individuals' ability to exert cognitive control processes in other tasks that place demands on attentional control processes. However, experimental work is necessary to address the question of whether there is transfer across different cognitive control tasks.

Separating Cognitive Control From Information Processing Speed

A critical difference between our and much of the prior work that examined whether different cognitive control tasks probe shared cognitive control processes, is that we use computational models that formally separate cognitive control processes from lower level processes, such as perceptual or response execution speed. In contrast, prior work employed subtraction methods, which may confound these processes.

It is critical to define information processing speed in the context of our research, however, because this construct has been defined and measured in a variety of ways (see Sweet, 2011). In the present study, we define information processing speed as the efficiency with which stimuli are perceptually processed and responded to in relatively simple tasks that place minimal demands on working memory and executive processes (e.g., Manard et al., 2014; Penke et al., 2010). A similar definition was used in a more recent study by Schubert et al. (2018), who applied a diffusion model to quantify individual differences in information processing speed. Relevant to the current work, these authors found that information processing speed accounted for a very small portion of shared variance between neural speed and higher level processes.

Our findings also suggest that the variance shared between two core cognitive control tasks cannot be reduced to individual differences in the efficiency with which people perceive

and respond to stimuli in simple tasks. However, our results do not entail that information processing speed at higher levels of processing would not explain a portion of individual differences in executive control processes. In line with other major frameworks of cognitive control (e.g., Gratton et al., 2018) we consider attentional processing speed, that is, the efficiency with which people select task-relevant information, as one way of characterizing a facet of cognitive control processes.

Which Cognitive Control Processes Are Common to the Flanker and Task-Switching Tasks?

Our modeling results corroborate a domain-general view of cognitive control. This domain-general process is typically construed as the ability to use online goals to selectively bias processing toward relevant information in a variety of tasks (e.g., Friedman & Miyake, 2017; Miyake & Friedman, 2012; Munakata et al., 2011).

Within each model, cognitive control processes are captured with activation weights, parameters that quantify how information that matches current goals is enhanced as well as how information that does not match current goals is inhibited. Even though prioritization and inhibition in our models are captured with separate parameters, this does not entail that these two processes are independent or even separable. That is, these parameters simply quantify the relative activation of task-relevant information and task-irrelevant activation. Together, they capture the degree to which task-relevant information is prioritized in the cognitive system in the presence of distracting information, and can be viewed as capturing levels of inhibitory control (e.g., Munakata et al., 2011). Broadly, our results are aligned with mainstream neural models of cognitive control that posit that the prefrontal cortex serves a critical role in the gating and maintenance of task-relevant information in working memory across tasks (e.g., Ott & Nieder, 2019).

Importantly, our results do not rule out that there are differences in how top–down control is implemented within the flanker and task-switching tasks. To this point, in Appendix B, we report the outcome of an additional parameter substitution analysis implemented on subsamples of the cross-validated data, which provide insight into how within-task prediction compares to across-task prediction. To summarize, we found that within-task predictive accuracy was higher than across-task predictive accuracy, indicating that there is some unique task-specific variance in the data. In our view, it follows from the structural differences of these tasks that there are some differences in how attentional control processes are engaged in them.

For instance, within the flanker task attentional control may support the focus of an attentional window (e.g., White et al., 2011), whereas in the task-switching task attentional control may support the prioritization of the current task set and/or the suppression of a competing task set. Currently, differences in processing dynamics between the two tasks are instantiated in the model equation, and how the model is fit to data based on the constraints of each task. That is, activation weights that quantify inhibitory processing, capture the degree to which flankers are activated on the flanker task, and capture the degree to which dimensions associated with the uncued task are activated in the task-switching task. Our

findings suggest that even in the presence of such task-specific effects, performance in these tasks is not entirely idiosyncratic but depends on a common attentional control factor.

Other Facets of Cognitive Control

The goal of our work was to examine whether basic attentional control processes are shared across tasks and, for this reason, we focused on measuring individuals' capacity to upweight task-relevant information and/or suppress task-irrelevant information. However, there are other facets of cognitive control. For instance, adaptation to conflict is also viewed as a potentially important facet of cognitive control (Egner & Hirsch, 2005; Gratton et al., 1992). In our task-switching and sequential flanker models, this facet of cognitive control is captured with rate parameters that quantify how quickly levels of activation of task-relevant or -irrelevant features change as a function of trial run. Our substitution analysis with these models (Appendix E) did not show an increase in predictive accuracy. Therefore, our modeling and analysis do not suggest that this aspect of cognitive control is shared across tasks (for similar conclusion, see Funes et al., 2010).

We acknowledge, however, that a failure to find that parameters generalize across models, like any null result, cannot be taken as conclusive evidence that no processes are shared across tasks. Such a result could reflect limitation of the sample, mispecification of the models, effects of context, or that there are (non)linear mappings of parameters across tasks. Therefore, future research could leverage parameter substitution analyses and alternative models to examine whether adaptation in cognitive control is shared across these tasks.

Another facet of cognitive control is strategies in how individuals approach complex tasks, and weigh speed and accuracy to improve performance. The goal of our analysis was to separate such strategies from attentional control; for this reason, we conceptually grouped speed and accuracy tradeoff strategies with other lower level processes, such as perceptual processing speed. However, an in-depth modeling analysis of individual differences in such strategies may also be of theoretical interest. As a basis for such a project, we conducted the parameter substitution analysis with threshold parameters (described in Appendix G). This analysis revealed that unpermuted substitution of threshold parameters increased predictive accuracy relative to a permuted substitution analysis. These results provide converging support for the view that there are stable individual differences in such strategies using an alternative model-based formal linking analysis (for similar result, see Hedge et al., 2021). As such, they may guide future work on how such strategies relate to other indices of higher level function (e.g., Chittka et al., 2009). Another contribution of this result is that it demonstrates that the parameter substitution approach introduced here can be instantiated in number of ways to test different hypotheses regarding which processes are shared or not shared across tasks.

Using Computational Models to Measure Hypothetical Constructs

Throughout this article, we underscored the strength of computational modeling approaches toward linking performance across tasks. Here, we highlight that, like in any modeling enterprise, our results can only be viewed through the lens of the models we chose. This is not unique to our approach; measuring unobservable constructs implies that theory and

measurement mutually constrain each other, a problem referred to as the "coordination problem" in philosophy of science (e.g., van Frassen, 2008; Kellen et al., 2020). Like all computational models, our models involve simplifying and auxiliary assumptions, some of which may be (and likely are) incorrect (e.g., Navarro, 2020).

We selected these models because they are based on vetted accumulator models that jointly capture accuracy and RTs for tasks with more than two response alternatives. In prior work, the task-switching model was extensively assessed on its ability to accommodate a range of phenomena in the Lumosity task-switching task, including task-switching costs as well as a change in performance as a function of training and individual differences in age (Steyvers et al., 2019). The flanker model is based on the task-switching model, and we found that it captures core individual differences in both accuracy and RTs across experimental conditions. Using parameter recovery simulations, we found that we could correctly recover cognitive control parameters in both models, even while there was systematic variation in other parameters in the model.

Furthermore, the fact that our top–down substitution analysis yields converging evidence for shared cognitive control processes across tasks, also provides evidence that these models are capturing core invariants. As discussed by Busemeyer and Wang (2000), "like strong inference, the generalization criterion is based on a priori predictions (made before observing the data) rather than post hoc fits (made after observing the data)." In other words, a test of these models is built-into our substitution analysis—it elucidates whether models' parameters have the potential to generalize, while eschewing standard concerns regarding overfitting.

To summarize, an inherent limitation of measuring unobservable constructs is that we cannot gain direct access to them in order to validate our cognitive models. Like others, we reference simulations and converging evidence for our assumption that these models do capture individual differences in attentional control. However, we also expect that follow-up work will use alternative models and analytic approaches to examine the robustness of our findings.

Evaluating Models Based on Their Capacity to Generalize Versus Fit to Data

Another critical aspect of our analysis is that we evaluate models based on their ability to generalize across tasks, as opposed to their capacity to fit data from a specific task. These approaches to model evaluation are technically and conceptually different—they serve different goals and may warrant different simplifying assumptions. For instance, although the models we use could be enhanced to capture a wider range of phenomena, we do not attempt to model every phenomenon reported in these tasks (e.g., posterror slowing). Such simplifying assumptions are desirable as a first step of our generalization approach because successful generalization requires some abstraction from specific properties of each task.

The fact that we evaluate models based on their capacity to generalize rather than fit data of each task, is also important for interpreting our comparison between the full cognitive control and reduced perceptual/motor variant of each model. This is because superior model fit to a particular task does not guarantee superior model generalization to a different task

(e.g., Pitt & Myung, 2002; Yarkoni & Westfall, 2017). Likewise, while we may expect that the cognitive control version of each model provides a superior fit to data from each task, there is no guarantee that the full cognitive control model would outperform the perceptual/motor model in predicting data on a different task. The relative performance of the cognitive control model depends on whether cognitive control parameters in this model capture invariants across tasks.

If cognitive control parameters capture no shared variance across the two tasks, the full cognitive control model could perform as well or worse than the perceptual/motor model. In fact, that is precisely what we find when we evaluate the predictive accuracy of the full cognitive control model that has parameters drawn from diffuse prior distributions (see: Primary Analyses section). This variant of the cognitive control model performs worse in predictive accuracy than the perceptual/motor model, underscoring the key point that levels of predictive accuracy depend on whether parameters in these models capture invariants or not.

Alternative Explanations

Our substitution approach is a type of covariation analysis toward linking models, and it remains logically possible that cognitive control parameters in our models are confounded with other processes. Despite this limitation, we can use our methodology to rule out a few alternative explanations. First, our modeling framework is designed to formally separate individual differences in processing speed and task strategies from cognitive control. As such, our results support the view that individual differences in strategic differences, processing speed, or low-level variables that may have downstream effects on these processes (e.g., individual differences in low-level vision), are not solely driving the observed results. Another low-level variable that could be confounded with cognitive control is passive priming (Mayr et al., 2003); however, the fact that each of the tasks uses four instead of two responses is known to substantially reduce the role of passive priming effects in cognitive control tasks (e.g., Blais et al., 2014).

Other potential confounding variables include individual differences in arousal, or motivation. If arousal (or motivation) increases information processing speed, its effects would be captured by parameters in the reduced perceptual/motor accumulator model (e.g., perceptual-encoding parameters), not the activation weights. However, if arousal (or motivation) is a stable individual difference that has downstream effects on cognitive control processes this could explain part of the shared variance captured by cognitive control parameters in the models.

We emphasize that our goal is not to rule out the role of variables that may affect cognitive control processes. For instance, one of the reasons we use the Lumosity sample is that there is a wide range of users who vary in age and, therefore, we assume, may also vary in their capacity to exert cognitive control (due to age-related cognitive decline). Our goal is not to make the claim that cognitive control is independent of all other variables. Rather it is to examine whether there is evidence that attentional control processes, which are likely jointly determined by a variety of other variables, are shared across two cognitive control tasks.

Another consideration is whether cognitive control parameters in our models capture control processes, or the learning of control processes as a function of training. First, we point out that processes on any task that involves extended practice, including standard laboratory tasks, will likely be affected by learning. Furthermore, the fact that a given ability, such as the capacity to exert cognitive control, crystallizes only after extensive practice on a given task is not problematic given our research goals. As an extreme illustration of this point, people who do not know how to do a task will not show individual differences in cognitive control. Similarly, in more nuanced cases people may need to achieve a sufficient level of mastery of a task for individual differences in higher level processes to be detectable. This view is consistent with theories of general intelligence, such as process overlap theory (Kovacs & Conway, 2019).

Directly relevant to our work, Steyvers and Schafer (2020) used Bayesian principal component analysis to examine covariation in learning trajectories across Lumosity tasks, including the two tasks used here. These authors found that learning trajectories between these two tasks are highly correlated with one another and load onto the same factor. This work provides provisional support for the view that the two tasks probe common latent processes. That is, it indicates that covariation across the two tasks reflects process specific covariation in attentional control processes and learning of them. Our work extends on this prior work by using computational models to quantify which cognitive processes are affected by training.

Collectively, our approach and results strongly support the view that we captured common cognitive control processes on the flanker and task-switching tasks. However, we hope that future work will leverage alternative models, analytic techniques and experimental designs to continue to examine this question. Indeed, a major strength of using computational models is that effects of extraneous variables can be formally incorporated into the task models.

Limitations and Future Directions

The parameter substitution approach is one of several possible ways of examining whether there are common latent processes across tasks. One advantage of our approach is that it is computationally simple. It contrasts with other linking approaches, such as Bayesian joint modeling, in which models are jointly fit to data from two tasks. Moreover, our analysis achieves a somewhat different goal than joint modeling analyses. That is, our goal is to examine whether we can generalize parameters from a model of one cognitive control task to a model of a structurally different cognitive control task. This analysis meets one of the highest benchmark for assessing the predictive accuracy of a model because it involves pure prediction, that is, predicting unseen data across different samples and tasks (Busemeyer & Wang, 2000). In contrast, in joint modeling approaches models are fit to data from both tasks, and prediction involves evaluating the predictive accuracy of models within tasks on held-out data.

Nevertheless, joint modeling approaches can build on our analysis and findings. For instance, whereas we find that cognitive control parameters can generalize across tasks, hierarchical Bayesian methods can be used to provide a more fine-grained analysis of

the degree to which model parameters in the two tasks are correlated, whether they are exchangeable, or whether (e.g., linear) transformations of parameters across the two tasks could improve model performance. Our own analysis suggests that linear transformations of parameters do not improve predictive accuracy (see Appendix F). Jointly fitting models to data from the two tasks could provide a more rigorous test of this question since data from both tasks would directly constrain parameter estimates in the two task models.

Likewise, an alternative method for formally linking models of tasks is with a clustering approach that examines whether parameters from different task models correlate with one another. Again, this type of analysis would not involve prediction of data on a different task, which is the goal of our parameter substitution analysis. Such analytic approaches can serve as useful exploratory tools; they can help researchers identify which model parameters are shared across tasks. Similarly, if researchers fail to find that parameters generalize across tasks, these type of exploratory approaches may help broaden the scope of models to help identify those that have the potential to generalize.

To summarize, our parameter substitution analysis provides support for the view that there are shared cognitive control processes in the flanker and task-switching tasks using a strong test of generalization. Joint modeling, and other linking approaches, may help uncover the degree to which these processes are shared, and outline a more nuanced picture of commonalities and differences in how processes are engaged in these tasks. Both lines of work help elucidate if and which cognitive processes are engaged in the two tasks and how they are engaged, and, consequently, can guide the development of unified models of the two tasks or impose constraints on existing integrative models (e.g., J. R. Anderson et al., 2004).

We also note that our findings and conclusions contrast with a recent study of Rey-Mermet et al. (2021). These authors used a hierarchical Bayesian–Wiener diffusion model to quantify individual differences in the difference in evidence accumulation on response congruent and incongruent trials in several cognitive control tasks (e.g., flanker, Stroop, and Simon task). Importantly, these authors found no evidence that there are stable individual differences in cognitive control, and concluded that their results challenge "the existence of attentional control as a psychometric construct." Our results suggest that this conclusion is premature. There are several important differences between our work and the work of Rey-Mermet et al. (2021), which might explain the discrepancy in our results and theirs. This includes differences in tasks, task models, linking approach, and sample size. For instance, our models include task-activation weights to separate cognitive control processes from perceptual speed accrual, whereas the models of Rey-Mermet et al. (2021) do not. Furthermore, our sample consists of 495 individuals, who on average completed 1,800 trials per task, whereas Rey-Mermet et al. (2021) had 263 individuals who, on average completed 224 trials per task. It is possible that these differences in models and sample size optimized our ability to detect individual differences in cognitive control. Nevertheless, this failure to reliably find evidence for common latent processes across tasks underscores the need for ongoing application of different formal modeling approaches toward studying cognitive control across tasks and contexts (e.g., Wall et al., 2021).

Finally, a major strength of using a large scale Lumosity sample is that it is heterogeneous and large, which optimizes our ability to detect individual differences in performance on the two tasks. However, as discussed, a limitation of using this sample is that we had no control over when people completed both tasks, and how they distributed practice of both tasks. Thus, our analysis cannot speak to which individual differences are tied to performance on these tasks. Future work may use experimental methods to examine which individual differences relate to performance on each task, as well as directly test the question of whether there is evidence for transfer across the two tasks.

Acknowledgments

Appendix A: Parameter Recovery

We implemented parameter recovery for the two task models in the following way. First, we obtained the range of parameter estimates in our sample from fitting models directly to the empirical data. We then varied each of the parameters by 10 stepsizes (e.g., increments of .1), such that their values spanned the full range of values obtained from our sample. For instance, we varied the cognitive control parameter τ, which captures cued task-activation in the task-switching task over the range .4–4 in increments of .4, yielding 10 parameter values in the generative model. For each value of τ, we independently varied each of the other parameters in the model while keeping the remaining parameters constant. For instance, we varied the parameter ξD, the accumulation parameter for shown stimuli on the range 1.2–3 in stepsizes of .2 when τ had a value of .4, and we repeated this for each value of τ while keeping the remaining parameters constant. We repeated this procedure for each paired combination of parameters in the models (36 and 21 pairs in the task-switching models, respectively). As noted, our goal was to examine whether we could reliably recover each of the parameters (τ) if there was variation in other parameters in the model (ξD). The result that we can still recover each key parameter in the model while other parameters are varied would indicate that parameters (e.g., related to cued task-activation and perceptual processing speed) are not confounded with one another.

We then simulated data from each of the models using these combinations of parameters. To match our simulated samples to our empirical samples, we sampled condition information and number of trials randomly from our sample with replacement. We used the same fitting procedure to estimate parameters in the synthetic data as we did to obtain best-fitting parameters from the empirical data.

The correlation matrices in Figure A1 show correlations between the parameter values estimated from the empirical data and their generative values (labeled "Recovered"; the τ parameter in our example). For each value of the recovered parameter (τ), we averaged its estimates when we varied the other parameter (ξD; labeled "Varied"). Therefore, correlations in the matrix indicate whether each parameter can be recovered while there is variation in the varied parameter.

To summarize, overall we found that all parameters could be accurately and consistently recovered. The only exception was the log of the rate parameter for the noncued task in the task-switching model (δ_γ), which captures how quickly the nonactivated task-set is suppressed as a function of trial run. However, we did not substitute these parameters between models, therefore, this does not affect our interpretation of our key findings. A second major result is that we found that noncognitive control and cognitive control parameters in our model are not confounded. That is, we consistently recovered each parameter in the model (e.g., those related to cognitive control) even when there was variation in other parameters in the model (e.g., those not related to cognitive control). This second analysis indicates that our assumption that cognitive control parameters do indeed capture cognitive control rather than variation in perceptual evidence accrual, or response thresholds is correct within our modeling framework.
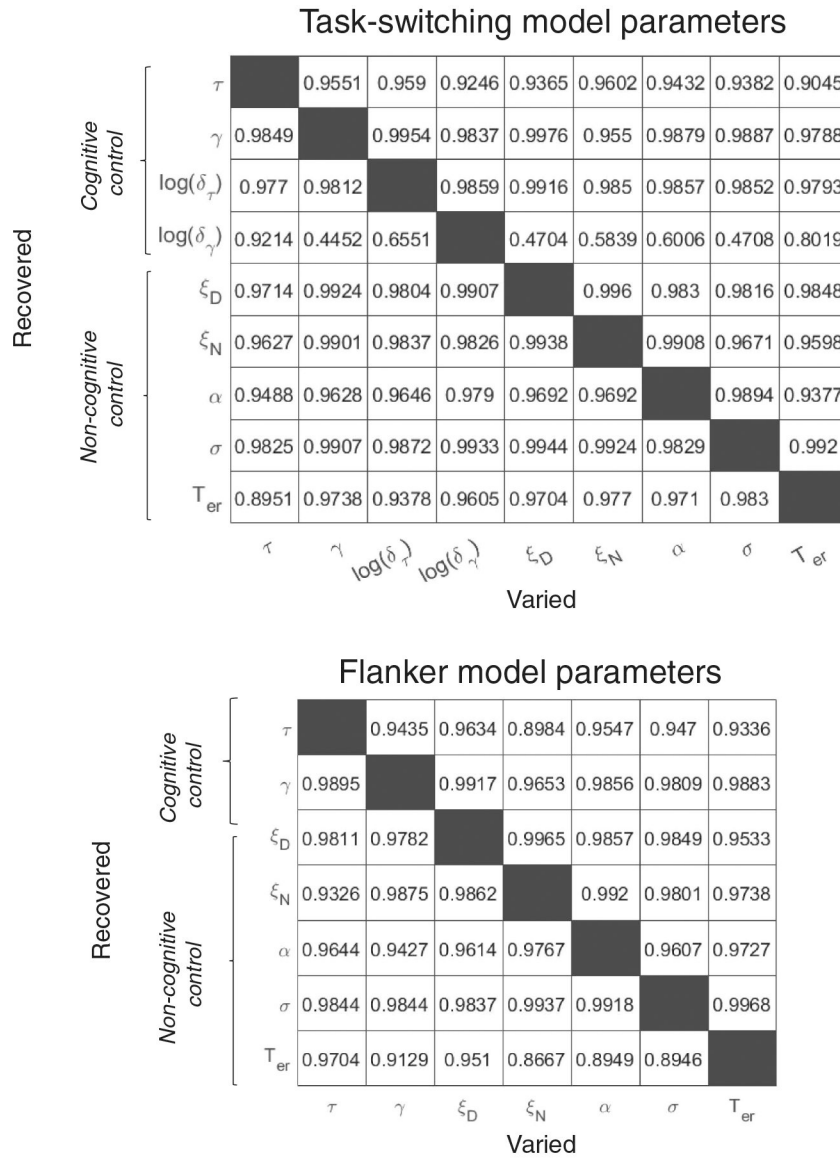
Task-switching model parameters

	τ	γ	$\log(\delta_\tau)$	$\log(\delta_\gamma)$	ξ_D	ξ_N	α	σ	T_{er}
τ		0.9551	0.959	0.9246	0.9365	0.9602	0.9432	0.9382	0.9045
γ	0.9849		0.9954	0.9837	0.9976	0.955	0.9879	0.9887	0.9788
$\log(\delta_\tau)$	0.977	0.9812		0.9859	0.9916	0.985	0.9857	0.9852	0.9793
$\log(\delta_\gamma)$	0.9214	0.4452	0.6551		0.4704	0.5839	0.6006	0.4708	0.8019
ξ_D	0.9714	0.9924	0.9804	0.9907		0.996	0.983	0.9816	0.9848
ξ_N	0.9627	0.9901	0.9837	0.9826	0.9938		0.9908	0.9671	0.9598
α	0.9488	0.9628	0.9646	0.979	0.9692	0.9692		0.9894	0.9377
σ	0.9825	0.9907	0.9872	0.9933	0.9944	0.9924	0.9829		0.992
T_{er}	0.8951	0.9738	0.9378	0.9605	0.9704	0.977	0.971	0.983	

Cognitive control: τ, γ, $\log(\delta_\tau)$, $\log(\delta_\gamma)$. Non-cognitive control: ξ_D, ξ_N, α, σ, T_{er}. (Recovered vertical; Varied horizontal)

Flanker model parameters

	τ	γ	ξ_D	ξ_N	α	σ	T_{er}
τ		0.9435	0.9634	0.8984	0.9547	0.947	0.9336
γ	0.9895		0.9917	0.9653	0.9856	0.9809	0.9883
ξ_D	0.9811	0.9782		0.9965	0.9857	0.9849	0.9533
ξ_N	0.9326	0.9875	0.9862		0.992	0.9801	0.9738
α	0.9644	0.9427	0.9614	0.9767		0.9607	0.9727
σ	0.9844	0.9844	0.9837	0.9937	0.9918		0.9968
T_{er}	0.9704	0.9129	0.951	0.8667	0.8949	0.8946	

Cognitive control: τ, γ. Non-cognitive control: ξ_D, ξ_N, α, σ, T_{er}. (Recovered vertical; Varied horizontal)

Figure A1. Parameter Recovery

Note. Results of parameter recovery simulations with the two cognitive control models. Correlations are between the generative and estimated parameter values for parameters shown in rows (Recovered). Varied parameters denote parameters that were varied for each value of the recovered parameter. Cognitive and noncognitive control refers to parameters that capture cognitive and noncognitive control processes in each of the tasks.

Appendix B: Evaluating Predictive Accuracy of Models Within Tasks

Here, we evaluate performance of these models within each of the tasks to show that they capture key trends in the data. To this end, we applied five-fold cross-validation to evaluate models within tasks. Cross-validation analysis has the advantage that it allows researchers to evaluate the predictive accuracy, as opposed to fit of models (Yarkoni & Westfall, 2017). Evaluating models based on their capacity to predict is desirable because adequate model fit does not always entail that models are capturing latent processes of interest. Instead, superior model fit may reflect overfitting to data, that is, erroneous fitting of error rather than substantive variance (Pitt & Myung, 2002). In contrast, effective prediction entails that models are capturing processing invariantts. For the cross-validation analysis, we analyzed data separately for each task. First, we randomly split the data of each individual into five equally sized subsamples (folds). Four folds were treated as the training set, to which we fitted the models and estimated best-fitting parameters. The remaining fold was treated as the test set, in which we predicted data. Specifically, we used best-fitting parameters from the training set to predict performance in the held-out test set. This procedure was repeated five time using each fold as the test set. We quantify predictive accuracy with R^2 and probability of correct prediction (for trial-level accuracy data, as explained below). These metrics of predictive accuracy are averaged across the five cross-validation iterations separately for reaction times and accuracy.
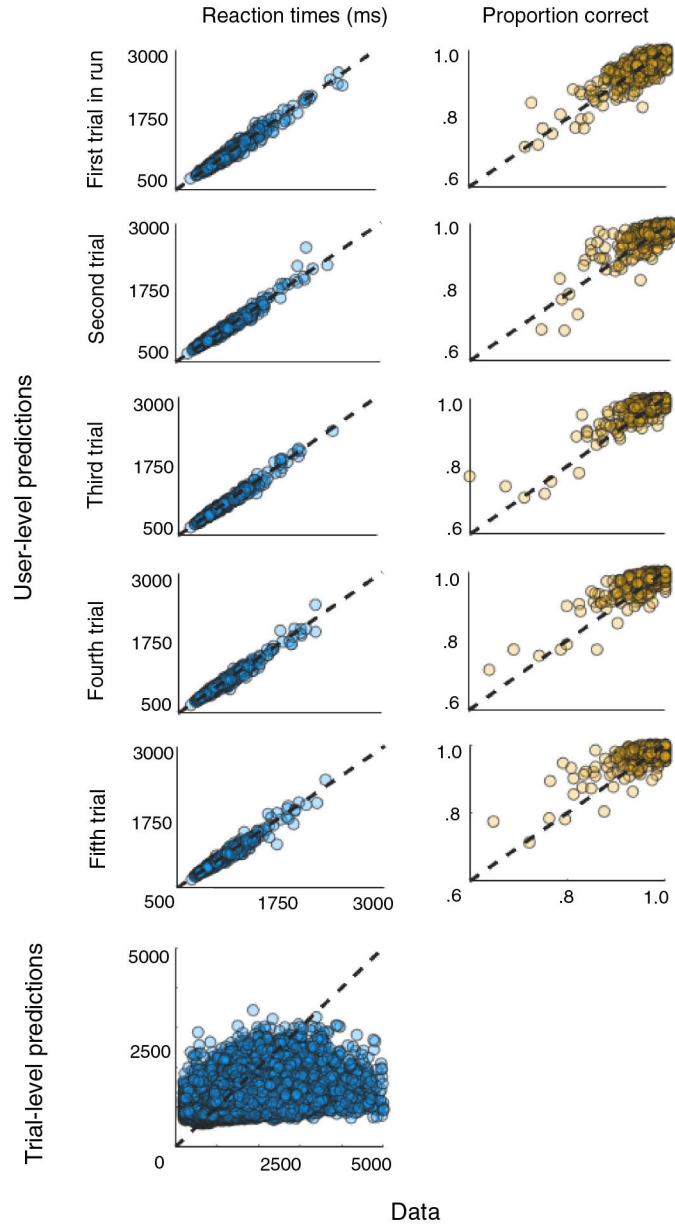
Figure B1. Task-switching Within-Task Cross-Validation

Note. Results from one iteration of the five-fold cross-validation analysis in the task-switching task. Each plot shows data in the validation set (*x*-axis) and the model predictions from data in the training set (*y*-axis). The first five panels show predictions at the level of individual users for each trial within a run of the same task. The bottom panel shows predictions of reaction times at the level of individual trials. Note that predictions for accuracy at the level of individual trials are omitted because these are dichotomous (see main text for measure of predictive accuracy).

Results of Cross-Validation

Task-Switching Task

Results from the cross-validation analysis are shown in Figure B1. We report model prediction at multiple levels, that is, the level of individual trials and individual users and conditions (i.e., trial with a run and congruency). Note that we omit plotting prediction of trial-level accuracy data because it is dichotomous, but report a measure of predictive accuracy below. For reaction times, at the level of trials we found an $R^2 = .37$ and at the level of individual users and conditions we found an $R^2 = .95$. For accuracy, we found an $R^2 = .66$ at the level of individual users and conditions. We measure our ability to predict accuracy at the level of trials with the probability of correctly predicting a correct or incorrect response on each trial. This probability was .96. In short, our results indicate that the model performs very well at predicting individual differences in performance on this task. Prediction at the level of individual trials is expectedly noisier but adequate.

Flanker Task

Results from the cross-validation analysis are shown in Figure B2. For reaction times, at the level of trials we found an $R^2 = .44$ and at the level of individual users and conditions we found an $R^2 = .98$. For accuracy, we found an $R^2 = .68$ at the level of individual users and conditions. The probability of correct prediction of accuracy at the level of individual trials was .97. Again, our results indicate that the model performs well at predicting individual differences and trial-level performance on the flanker task.

Results of Across-Task Prediction

Here, we report how prediction within tasks compares to prediction when using subsets of data from our cross-validation analysis. For simplicity, we focus on comparisons at level of individual users using the full cognitive control models of each task, and we report results from the unpermuted and permuted analyses.

When using the task-switching model as the target model, for the unpermuted analysis, we found an $R^2 = .74$ and $R^2 = .29$, for RTs and accuracy, respectively. For the permuted analysis, we found an $R^2 = .01$ and $R^2 = .05$ for RTs and accuracy, respectively. When using the flanker model as the target model, for the unpermuted analysis, we found an $R^2 = .76$ and $R^2 = .28$, for RTs and accuracy, respectively. For the permuted analysis we found an $R^2 = .01$ and $R^2 = .04$ for RTs and accuracy, respectively. Together, these results provide provisional support for the view that the two tasks measure some of the same processes. Notably, we also find that across-task prediction is lower than within-sample prediction, which suggests that there is unique task-specific variance in the data.
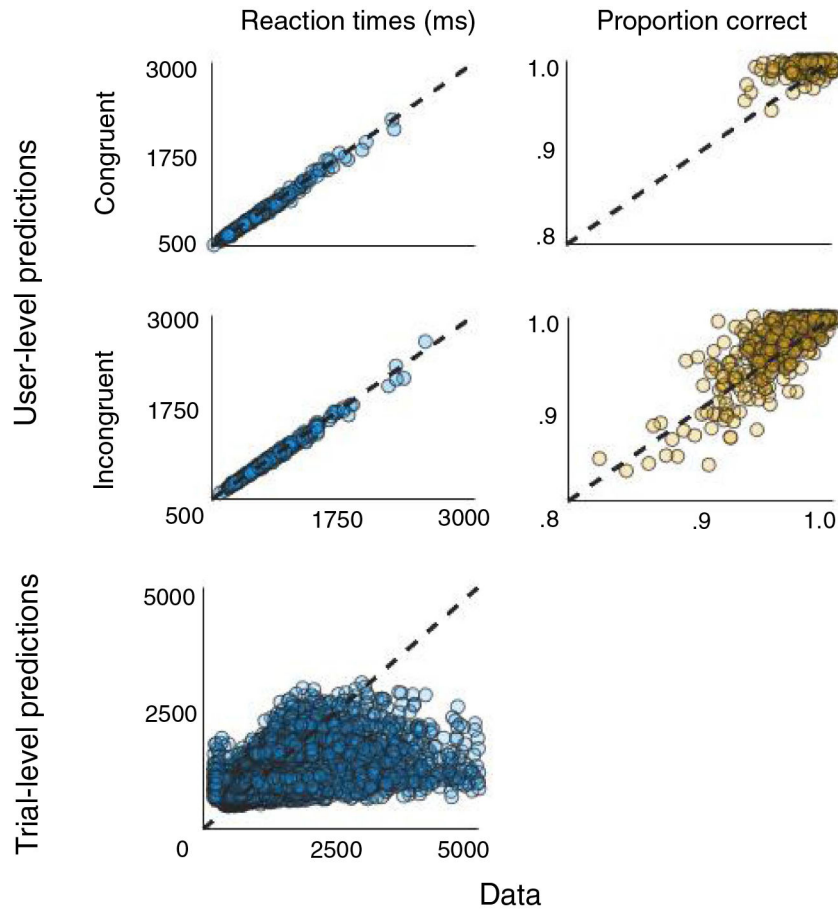
Figure B2. Flanker Within-Task Cross-Validation

Note. Results from one iteration of the five-fold cross-validation analysis in the flanker task. Each plot shows data in the validation set (*x*-axis) and the model predictions from data in the training set (*y*-axis). The first two panels show predictions at the level of individual users for response congruent and incongruent conditions. The bottom panel shows predictions of reaction times at the level of individual trials. Note that predictions for accuracy at the level of individual trials are omitted because these are dichotomous (see main text for measure of predictive accuracy).

Appendix C: Deviations for Unpermuted and Permuted Substitution

In this section, we show an alternative way of visualizing predictive accuracy when comparing unpermuted and permuted substitution with the full cognitive control model in our primary analyses. For this analysis, we analyze deviations from the parameter substitution analysis and observed data for RTs and proportion of errors separately using root-mean-squared deviation (RMSD). Figure C1 shows the results when the RMSD (shown as error bars in the Figure) is assessed at the level of trials (left panels) as well as the level of users after averaging the observed data and predictions across trials within each experimental condition (right panels).

As shown in Figure C1, unpermuted and permuted substitution will make the same average predictions, but deviate when predicting data on the target task at the level of trials and users. In both cases, we find that unpermuted predictions outperform permuted prediction as assessed by RMSD (see Primary Analyses in the main text, for formal analysis).

Note that we present this analysis for visualization purposes rather than a core analysis because it does not jointly capture prediction at the level of RTs and accuracy.
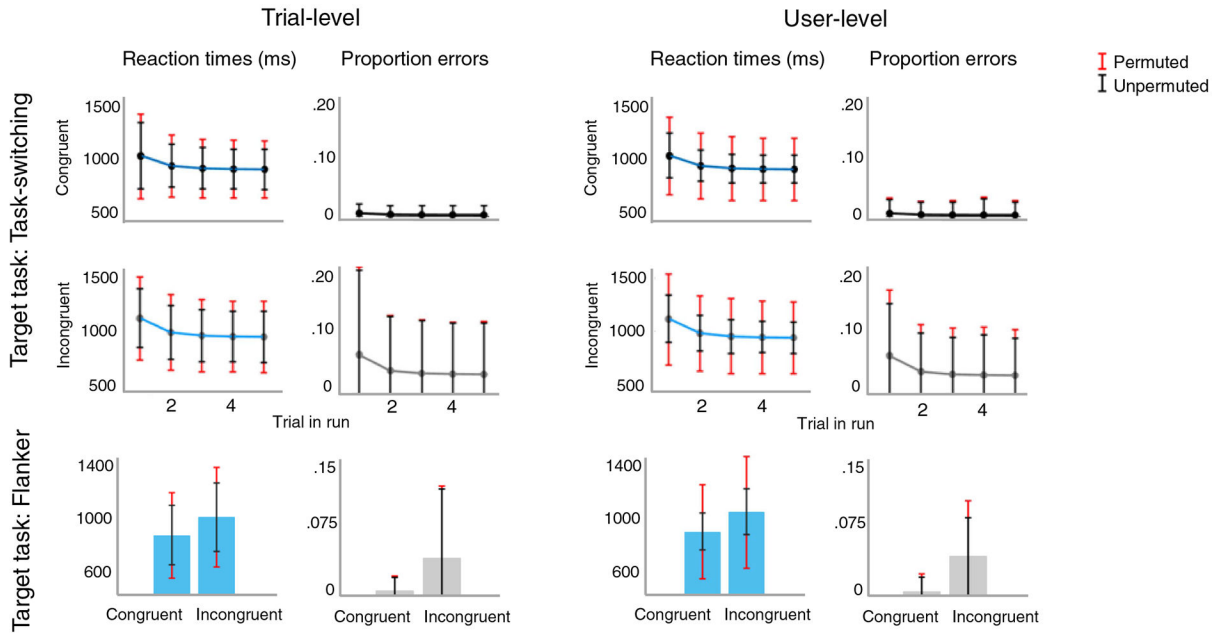
Figure C1. Alternative Visualization of Parameter Substitution Results
Note. Results from the unpermuted and permuted analyses with the full cognitive control model. These plots show the average predictions for the unpermuted and permuted analyses as well as the deviations of these predictions from the observed data on the target task. Error bars represent root-mean-squared deviations between predicted and observed data assessed at the trial-level (left panels) and user-level (right panels). Larger error bars indicate lower predictive accuracy.

Appendix D: Model Extension: Learning Model of Cognitive Control

The results reported in the main text indicate that cognitive control processes may be shared across tasks. However, our large scale sample also permits us to examine whether processes that determine a change in these cognitive control processes as a function of learning are shared across tasks. In the following sections, we describe both of the *learning* variants of the cognitive control models of each task, and present results from the parameter substitution analysis.

Learning Task-Switching Model

The learning variant of the task-switching model is identical to the one developed by Steyvers et al. (2019). As such, it is similar to the cognitive control task-switching model,

with the exception that activation weights and rate parameters can change as a function of training. Thus, as before, there are two activation weights that capture how processing of features of the cued and uncued task varies as a function of trial run. This is given by following equations:

$$A_{k,i} = B_{k-1} + (v - B_{k-1}) \times (1 - e^{-ig}).$$ (D1)

$$B_{k,i} = A_{k-1} + (u - A_{k-1}) \times (1 - e^{-ih}).$$ (D2)

Notably, Equations D1 and D2 are nearly identical to Equations 1 and 2 in the main text, respectively. That is, $A_{k,i}$ in Equation D2 represents levels of activation of the cued task on a given trial i within a run of trials k, which starts at a baseline level of activation (B_{k-1}), which was achieved on the previous run of trials when the currently cued task was the uncued task. Activation levels of the cued task increase with each trial toward an asymptotic levels of activation (v), and this rate of change is assumed to change exponentially with rate g. Similarly, $B_{k,i}$ in Equation D2 shows that activation levels of the currently uncued task on a given trial starts at an asymptotic level of activation that was achieved in the previous run of trials (A_{k-1}) and decreases toward a baseline level of activation. This change in activation also follows an exponential growth function and is determined by a separate rate parameter h.

Importantly, in this version of the model, asymptotic activation, baseline activation, and rate parameters can themselves change as a function of training. This property of the model captures the fact that with increased practice on a given task people may become better at prioritizing task-relevant features (increase in v), deprioritizing task-irrelevant features (decrease in u) and/or faster at adapting these control settings as a function of trial run (increase in g and/or h). These changes in activation functions and rate parameters are also captured with an exponential growth function, and are given by the following equations:

$$v_m = \tau_v + (\gamma_v - \tau_v) \times (1 - e^{-\delta_v(m-1)}).$$ (D3)

$$u_m = \tau_u + (\gamma_u - \tau_u) \times (1 - e^{-\delta_u(m-1)}).$$ (D4)

$$\log(g)_m = \tau_g + (\gamma_g - \tau_g) \times (1 - e^{-\delta_g(m-1)}).$$ (D5)

$$\log(h)_m = \tau_h + (\gamma_h - \tau_h) \times (1 - e^{-\delta_h(m-1)}).$$ (D6)

In the above equations, the subscript m denotes the number of the training session. As we discuss later, we model data from the first 60 sessions of each individual's training. τ in each model denotes the starting value of each parameter, γ denotes the value of the parameter

obtained after training, and δ denotes the rate at which parameters change as a function of training.

Learning Flanker Model

The learning variant of the flanker model is also identical to the cognitive control flanker model, with the exception that activation functions can change as a function of training. More precisely, the two activation functions for the target (v) and flankers (u) are given by the following equations:

$$v_m = \tau_v + (\gamma_v - \tau_v) \times (1 - e^{-\delta_u (m-1)}). \tag{D7}$$

$$u_m = \tau_u + (\gamma_u - \tau_u) \times (1 - e^{-\delta_u (m-1)}). \tag{D8}$$

As before, the subscript m denotes the number of the training session, τ in each model denotes the starting value of each parameter, γ denotes the value of the parameter obtained after training, and δ denotes the rate at which parameters change as a function of training. In the next sections, we explain how we leverage the perceptual/motor and cognitive control task models and parameter substitution analysis to examine whether there is evidence for shared cognitive control processes in the task-switching and Flanker tasks.

Technical Details of Modeling and Analysis

In this section, we present results from modeling and parameter substitution analysis using a model extension of each cognitive control task model that captures effects of learning on cognitive control. We report results from our primary and secondary analysis. As before, we apply our substitution analyses to examine whether there is evidence for shared learning of cognitive control processes in the two tasks.

Characteristics of the Sample

We used the same sample of users as in the first analysis, with the exception that we analyzed their data from the 1st to the 60th game session in order to capture changes in cognitive control as a function of training.

Parameter Estimation and Substitution Analysis

The model fitting and parameter substitution approach was identical to the one used for the reduced version of the models.

Results

Once again, statistical comparisons in our primary analysis revealed that the cognitive control model with learning helped with prediction over and above the perceptual/motor model, and both models captured individual differences within and across tasks. Likewise, statistical comparisons in our secondary analysis indicate that the full cognitive control

model with unpermuted analysis outperforms the full cognitive control model with mixed parameter substitution.

Target Task: Task-Switching

Primary Analysis.—There was a significant difference in the PLL of the perceptual model with permuted and unpermuted parameters, $t(494) = 22.96$, $p < .0001$; $z = 18.34$, $p < .0001$; 94% of sample; favoring the target model with unpermuted ($\bar{X} = -1769$, SEM = 52) versus permuted ($\bar{X} = -3554$, SEM = 67) parameters. Similarly there was significant difference in the PLL of the cognitive control model with permuted and unpermuted parameters, $t(494) = 34.4$, $p < .0001$; $z = 18.48$, $p < .0001$; 97% of sample; favoring the cognitive control model with unpermuted ($\bar{X} = -654$, SEM = 69) versus permuted parameters ($\bar{X} = -3271$, SEM = 77). These results indicate that both the perceptual/motor and cognitive control models captured individual differences in the data.

We also found that the cognitive control model yielded a large PLL than the perceptual/motor model both when parameters were permuted, $t(494) = 5.56$, $p < .0001$; $z = 4.2$, $p < .0001$; 53% of sample, and unpermuted, $t(494) = 34.4$, $p < .0001$; $z = 18.49$, $p < .0001$; 85% of sample. For the critical comparison, we tested the difference in the likelihood ratio of the PLL between the perceptual/motor and cognitive control model when parameters were permuted and unpermuted. This test revealed that the likelihood ratio was higher, $t(494) = 11.97$, $p < .0001$; $z = 12.2$, $p < .0001$; 73% of sample; indicating more support for the cognitive control model when data were unpermuted ($\bar{X} = 1115$) versus permuted ($\bar{X} = 282$).

Secondary Analysis.—With mixed parameter substitution, we found that the full cognitive control model with unpermuted parameters ($\bar{X} = -654$, SEM = 69) outperformed the cognitive control task-switching model when cognitive control parameters were permuted across individuals ($\bar{X} = -1243$, SEM = 94; $t(494) = 6.31$, $p < .0001$; $z = 6.65$, $p < .0001$; 63% of sample.

Target Task: Flanker

Primary Analysis.—There was a significant difference in the PLL of the perceptual model with permuted and unpermuted parameters, $t(494) = 14.75$, $p < .0001$; $z = 14.89$, $p < .0001$; 83% of sample; favoring the target model with unpermuted ($\bar{X} = -2721$, SEM = 105) versus permuted ($\bar{X} = -4309$, SEM = 153) parameters. Similarly, there was significant difference in the PLL of the cognitive control model with permuted and unpermuted parameters, $t(494) = 23.13$, $p < .0001$; $z = 18.6$, $p < .0001$; 96% of sample; favoring the cognitive control model with unpermuted ($\bar{X} = 82$, SEM = 64) versus permuted parameters ($\bar{X} = -2519$, SEM = 112). These results indicate that both the perceptual/motor and cognitive control models captured individual differences in the data.

We also found that the cognitive control model yielded a large PLL than the perceptual/motor model both when parameters were permuted, $t(494) = 24.17$, $p < .0001$; $z = 16.83$, $p < .0001$; 83% of sample, and unpermuted, $t(494) = 29.27$, $p < .0001$; $z = 19.19$, $p < .0001$; 99% of sample. For the critical comparison, we tested the difference in the likelihood ratio of the PLL between the perceptual/motor and cognitive control model when parameters

were permuted and unpermuted. This test revealed that the likelihood ratio was higher, $t(495) = 16.4$, $p < .0001$; $z = 14.49$, $p < .0001$; 83% of sample; indicating more support for the cognitive control model when data were unpermuted ($\bar{X} = 2803$) versus permuted ($\bar{X} = 1790$).

Secondary Analysis.—With mixed parameter substitution, we found that the full cognitive control model with unpermuted parameters ($\bar{X} = 82$, SEM = 64) outperformed the cognitive control task-switching model when cognitive control parameters were permuted across individuals ($\bar{X} = -1219$, SEM = 107; $t(494) = 12.7$, $p < .0001$; $z = 14.2$, $p < .0001$; 79% of sample.

Summary of Results

Together, these results indicate that cognitive control and learning parameters increase predictive accuracy of the target model and capture individual differences in the data. As such, the results of this analysis corroborate the view that a change in cognitive control processes as a function of learning is shared across the two tasks.

Appendix E: Flanker Model With Sequential Effects

The flanker model with sequential effects is compatible with the view that inhibiting response incongruent flankers engages inhibitory processes differently, or to a greater extent than the processing of response congruent flankers. As such, it differs from the baseline cognitive control flanker model (described in the main text) in two ways. First, rather than having a single activation weight for congruent and incongruent flankers, there are separate activation weights for congruent and incongruent flankers in the sequential effects model. Thus, there are three activation weights for the target, and congruent, and incongruent flankers. Second, we assume that sequential effects in the flanker task reflect the degree to which the processing of congruent or incongruent flankers changes as a function of trial run. For instance, it is possible that with each consecutive trial of incongruent flankers, people filter out incongruent flankers more effectively (e.g., by narrowing an attentional window), whereas with each consecutive trial of congruent flankers, people process congruent flankers to a greater extent (e.g., by broadening an attentional window). In order to preserve parameter identifiability, we make the simplifying assumption that processing of the target is constant as a function of trial run. Activation weights for congruent and incongruent flankers are given by the following equations:

$$CF_{k,i} = IF_{k-1} + (\phi - IF_{k-1}) \times (1 - e^{-i\delta_\phi}). \tag{E1}$$

$$IF_{k,i} = CF_{k-1} + (\gamma - CF_{k-1}) \times (1 - e^{-i\delta_\gamma}). \tag{E2}$$

In Equation E1, the activation level of the congruent flanker ($CF_{k,i}$) on a given trial i within a run of trials k, starts at a baseline level of activation (IF_{k-1}), which was achieved on the previous run of trials ($k - 1$) when the currently congruent flanker was the incongruent flanker. Activation of the congruent flanker can increase with each trial toward

an asymptotic level of activation, which is quantified with parameter φ. The rate at which activation of the congruent flanker increases toward asymptote is assumed to be exponential and is determined by a rate parameter δ_ϕ. Similarly, in Equation E2, the activation levels of the incongruent flanker on a given trial ($IF_{k,i}$) starts at an asymptotic level of activation that was achieved in the previous run of trials (CF_{k-1}) and decreases toward a baseline level of activation, which is quantified with parameter γ. This change in activation also follows an exponential growth function and is determined by a separate rate parameter δ_γ. Target stimuli are captured with parameter τ.

For this parameter substitution analysis, we assumed that weights associated with congruent and incongruent flankers, mapped onto weights associated with the cued and uncued task, respectively. As noted in the main text, we did not find that this model outperformed the simpler baseline cognitive control Flanker model. PLL when the target task was the flanker task = −7,896, PLL when the target task was the task-switching task = −6,710. Note that the results of our analysis are circumscribed by the modeling framework we use and do not rule out the possibility that a sequential effects Flanker model could not improve prediction in principle.

Appendix F: Linear Transformations of Parameters

We also examined whether linear transformations of parameters across tasks improved prediction. For this analysis, we ran a linear regression to quantify the linear relationship between each parameter across the flanker and task-switching tasks. More precisely, we averaged parameters across 30 chains for each subject, separately for each task. We then fit a linear model using the fitlm Matlab function to estimate an intercept and slope parameter, where individual parameter values on the source task were used to predict individual parameter values on the target task. We used statistically significant coefficients to transform parameters across the two tasks, and calculated the predictive accuracy of each model using our parameter substitution analysis with these transformed, rather than untransformed values. We did not find that these linear transformations improved prediction over-and-above the baseline cognitive control model of each task (presented in main text). PLL when the target task was Flanker = 205, PLL when the target task was task-switching = −442.9522.

Appendix G: Speed and Accuracy Tradeoff Strategies

Our research goal was to focus on a specific facet of cognitive control, that is, attentional control, which we defined as the capacity to upweight task-relevant and suppress task-irrelevant information. However, there are potentially other facets of cognitive control. For instance, speed and accuracy tradeoff strategies by definition capture how people strategically approach the tasks and, therefore, can also be seen as a form of cognitive control. Although not central to our research question, we report the results of a parameter substitution analysis that examines whether speed and accuracy tradeoff strategies are shared across these two tasks. This analysis complements prior work that examines individual differences in speed and accuracy strategies using a model-based, formal linking analysis.

Within our accumulator modeling framework, speed and accuracy strategies are quantified with the threshold parameter α, which captures the amount of perceptual evidence individuals accumulate before making responses. To examine whether these strategies are common across the two tasks, we conducted the unpermuted and permuted version of the parameter substitution analysis with the threshold parameter using the full cognitive control model of each task. Specifically, we either swapped the same individual's threshold parameter (unpermuted analysis) or a different individual's threshold parameter (permuted analysis) from the source task to predict performance on the target task. Critically, in this analysis all of the remaining parameters in the cognitive control model of each task were from the same individual. For instance, for the unpermuted analysis, all of Bill's parameters in the full cognitive control model from target (e.g., task-switching) task were used to capture the target (e.g., task-switching) data, except for the threshold parameter which was swapped in from Bill's source (e.g., flanker) task. In contrast, for the permuted analysis, all of Bill's parameters in the full cognitive control model from target (e.g., task-switching) task were used to capture the target (e.g., task-switching) data, except for the threshold parameter which was swapped in from Sue's source (e.g., flanker) task. This analysis revealed that the unpermuted analysis yielded higher predictive accuracy than the permuted analysis both when the target task was the task-switching task, unpermuted PLL $\bar{X} = 393$, SEM = 27 and permuted PLL $\bar{X} = 334$, SEM = 26; $t(494) = 9.21$, $p < .0001$, and when the target task was the flanker task, unpermuted PLL $\bar{X} = 567$, SEM = 27 and permuted PLL $\bar{X} = 486$, SEM = 21; $t(494) = 6.35$, $p < .0001$. Together, these results provide converging support for the view that other facets of cognitive control are also shared across the tasks, particularly, speed and accuracy strategies.

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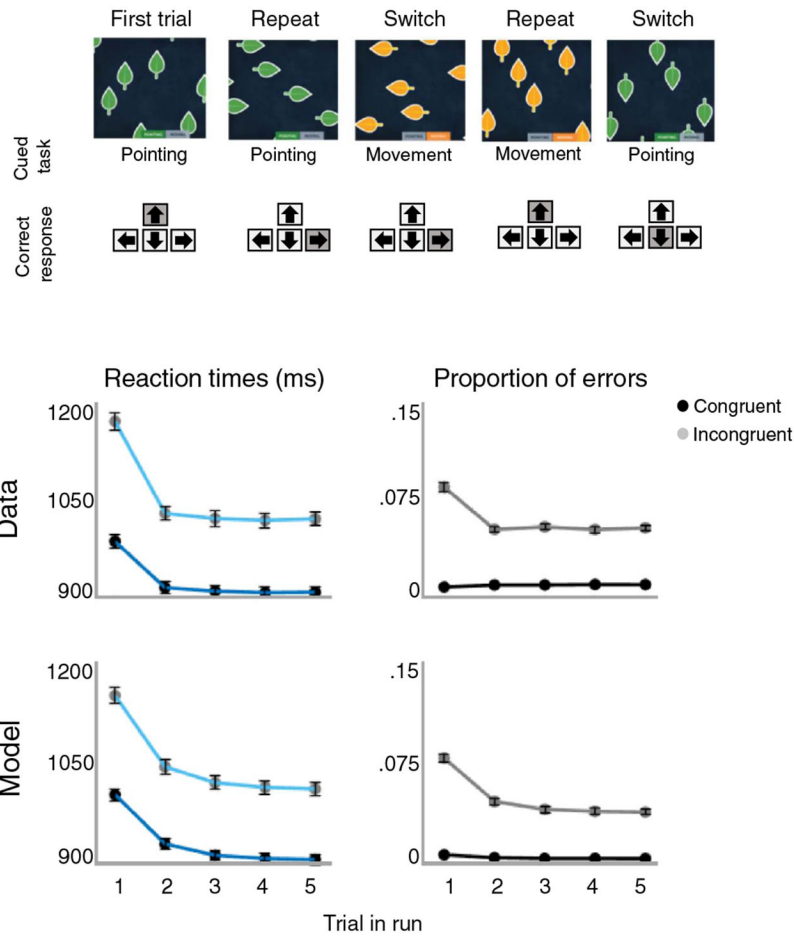
Figure 1. Example Trials and Aggregate Data and Model Fits in the Task-Switching Task

Note. The upper panel shows an example sequence of trials from the task-switching task. On each trial participants see a set of leaves that are moving and pointing in one of four possible directions (left, right, up, or down). The color of the leaves and a written prompt, cues participants to complete one of two tasks, which is to respond either on the moving (green) or pointing (orange) direction of the leaves. The lower panel shows the typical pattern of results, which is that people become progressively faster and make fewer errors as they complete more consecutive trials of the same task. The plotted data are the same as those used in the modeling here. We include both the observed data and the model fits to those data.
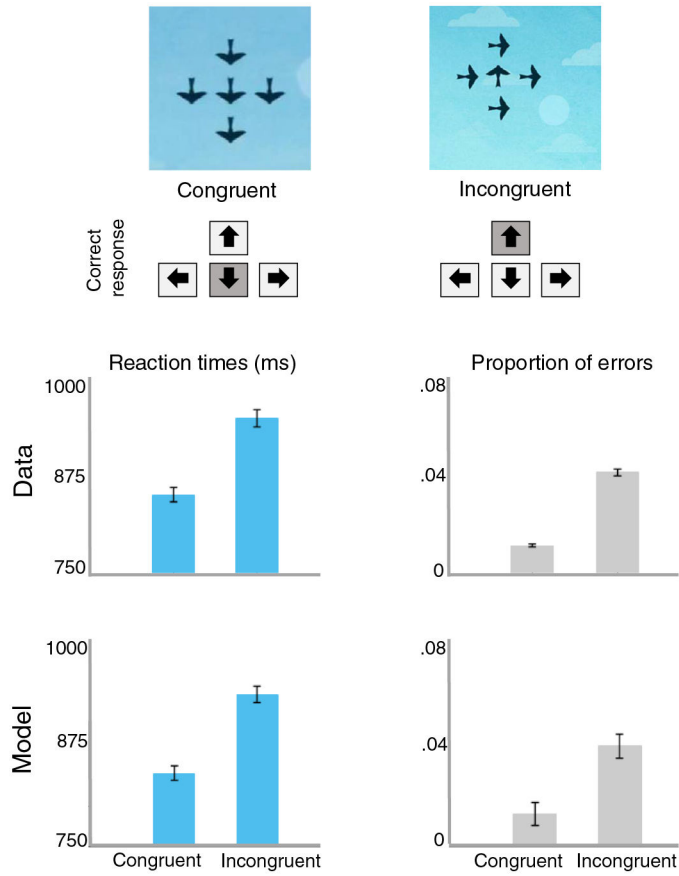
Figure 2. Example Trials and Aggregate Data and Model Fits in the Flanker Task

Note. The upper panel displays example trials from the flanker task. On each trial participants are shown a configuration of five birds and are instructed to respond to the pointing direction of the (target) bird in the center and disregard the pointing direction of the flanking birds. On congruent trials, the target and flanking birds point in the same direction, whereas on incongruent trials the target and flanking birds point in different directions. The lower panel shows the typical pattern of effects obtained in the flanker task, with longer reaction times and higher proportion of errors on incongruent than congruent trial. The plotted data are the data used for the modeling here. We include both the observed data and the model fits to those data.
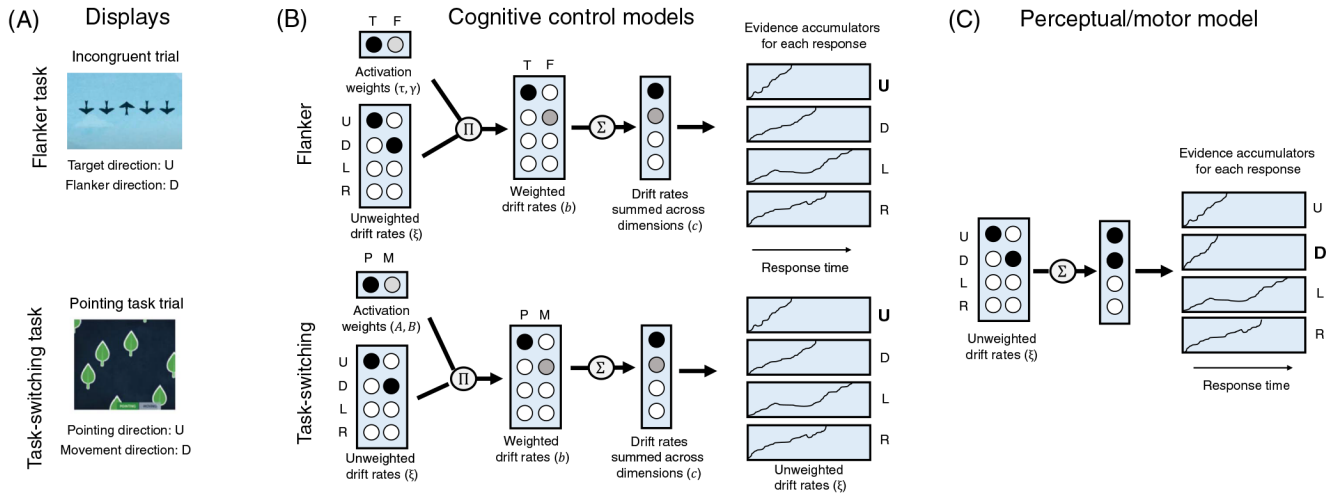
Figure 3. Model Schematics

Note. Example displays from the flanker and task-switching tasks and schematics of each task model. Panel (A) shows an example display on a Flanker incongruent trial and an example display on the task-switching task in which the cued (pointing) task and the uncued (movement) task potentiate different responses. Panel (B) shows the full cognitive control model of each task. Black circles denote high levels of activation, and white circles denote low levels of activation (with gradations in between). The perceptual input features (ξ) are weighted by task activation (τ and γ in the flanker model and *A* and *B* and in the task-switching model), and the resulting weighted activations (*b*) are summed across dimensions to produce the drift rates (*c*) for the four response alternatives. The evidence accumulator for the *U* (up) response reaches the decision threshold first and determines the response choice and response time. Panel (C) shows a schematic of the reduced perceptual/ motor model of each task, which does not capture cognitive control processes. In this scenario, performance on the flanker and task-switching tasks is determined by the rate of perceptual evidence (ξ) accrual for displayed features (up and down), and undisplayed stimulus features (left and right), as well as other parameters in the simple accumulator model. U = up, D = down, L = left, R = right, T = target, F = flanker, P = pointing, M = moving. Adapted with permission from "A large-scale analysis of task switching practice effects across the lifespan," by M. Steyvers, G. E. Hawkins, F. Karayanidis, and S. D. Brown, 2019, *Proceedings of the National Academy of Sciences, 116*(36), pp. 17735–17740 (https://dx.doi.org/10.1073/pnas.1906788116).
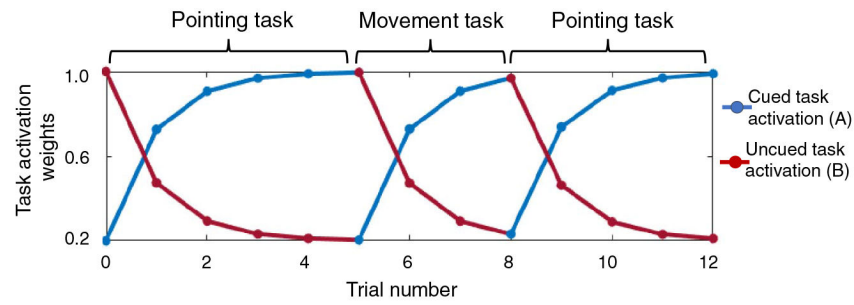
Figure 4. Activation Functions in the Task-switching Task

Note. Example of how activation weights of the cued task (A) and uncued task (B) change as a function of trial run and switches between tasks in the task-switching task. Adapted with permission from "A large-scale analysis of task switching practice effects across the lifespan," by M. Steyvers, G. E. Hawkins, F. Karayanidis, and S. D. Brown, 2019, *Proceedings of the National Academy of Sciences, 116*(36), pp. 17735–17740 (https://dx.doi.org/10.1073/pnas.1906788116).
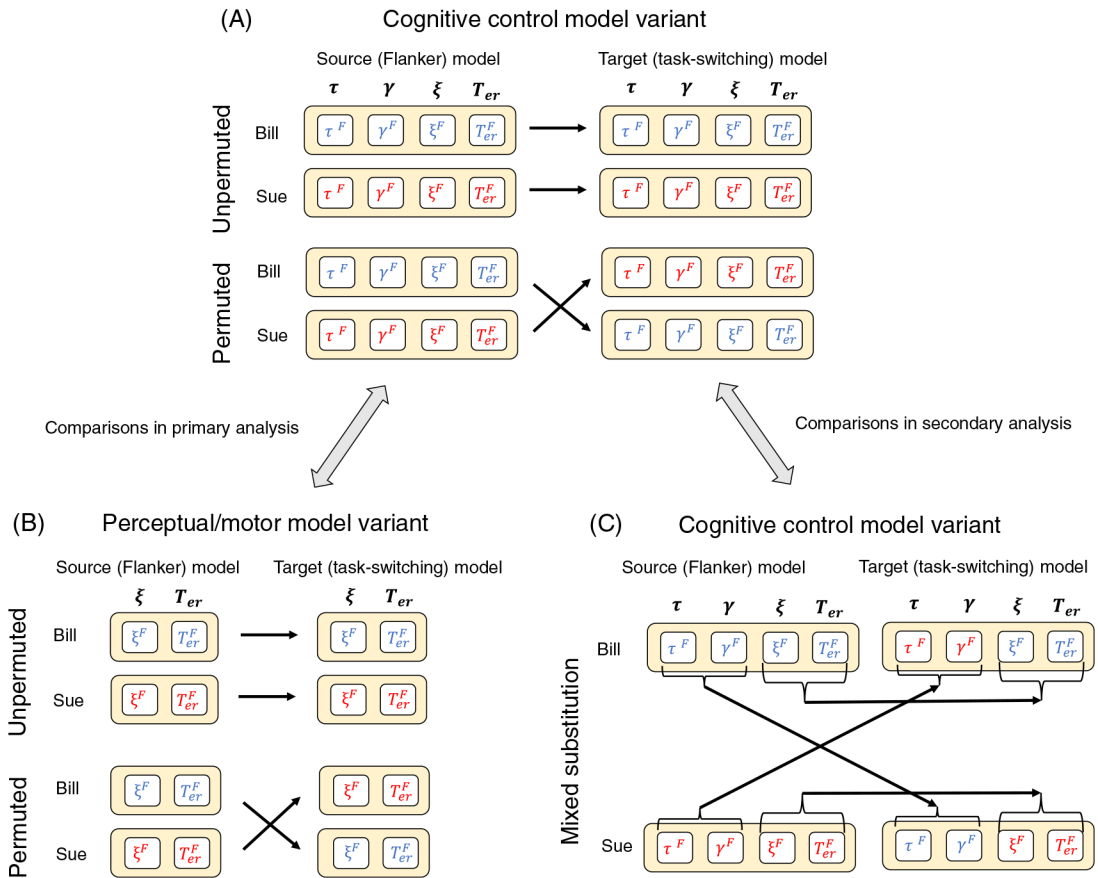
Figure 5. Schematic of Each Variant of the Substitution Analysis

Note. For simplicity, we show only a subset of control and noncontrol parameters from each model. In these examples, the source task is always the flanker task, however, we repeated our analysis with the flanker and the task-switching task as the source task to ensure that our parameters substitution results were robust. Also, for simplicity, we consider substitutions across two people, Bill and Sue instead of the full sample of users. For each unpermuted analysis, Bill's (blue) and Sue's (red) parameter estimates from the source task are used to predict their data in the target task. For each permuted analysis Bill's (blue) and Sue's (red) parameter estimates from the source task are used to predict the other person's data in the target task. Panel A shows unpermuted and permuted substitution with the full cognitive control model of each task. Panel B shows unpermuted and permuted substitution with the reduced perceptual/motor model of each task, which excludes the cognitive control parameters. Panel C shows the mixed parameter substitution analysis with the full cognitive control model. In this final analysis, cognitive control parameters are permuted across individuals, whereas noncognitive control parameters are not.
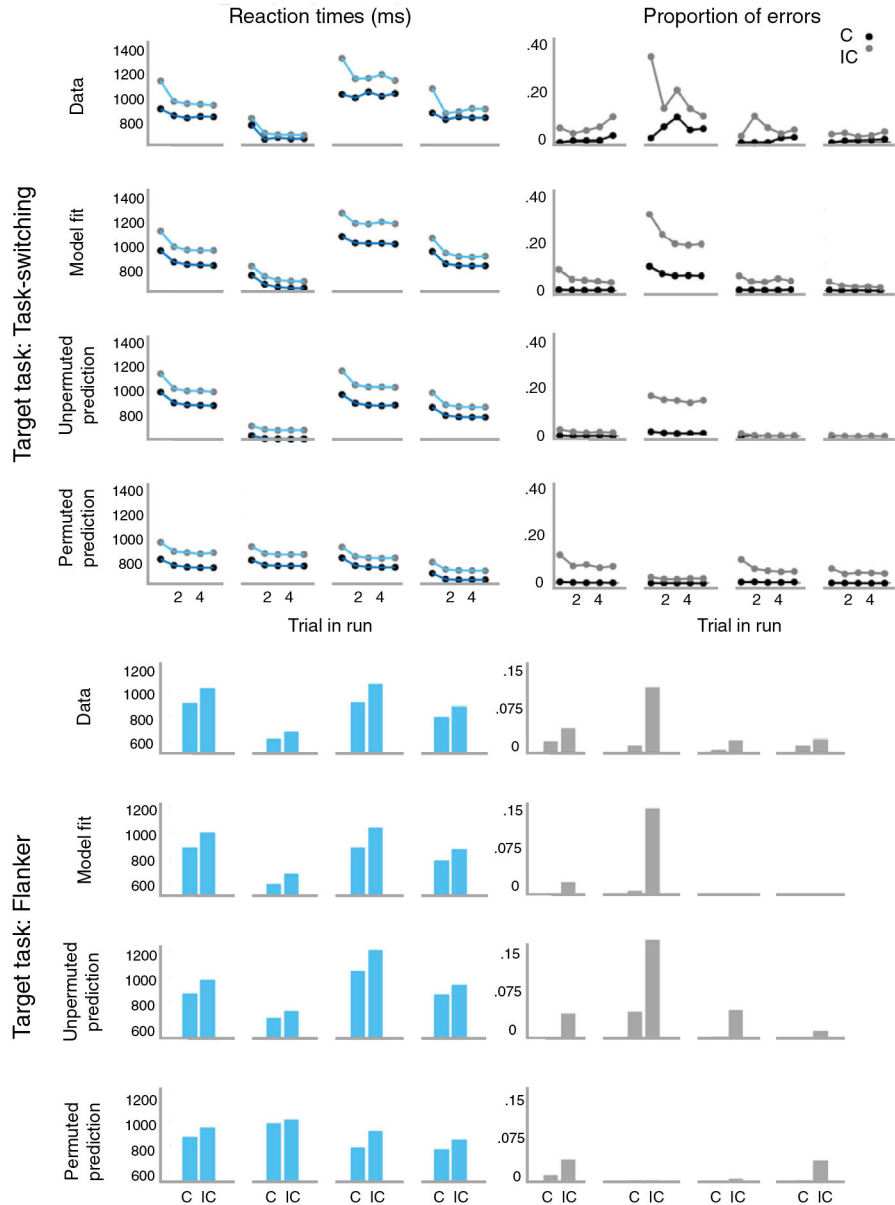
Figure 6. Example Data, Model Fits and Model Predictions for Four Lumosity Users
Note. Each column corresponds to a user's reaction times (left panel) and accuracy (right panel) for the task-switching and flanker tasks. Rows labeled data, show the observed data of each user. Rows labeled model fit model fit show the model fit of the target model to the target data. Finally, rows labeled unpermuted and permuted prediction show predictions of behavior on the target task, using parameters from the source model when parameters are unpermuted and permuted across individuals, respectively. For the permuted predictions, we show the outcome from a single permutation for illustration. C = congruent, IC = incongruent.
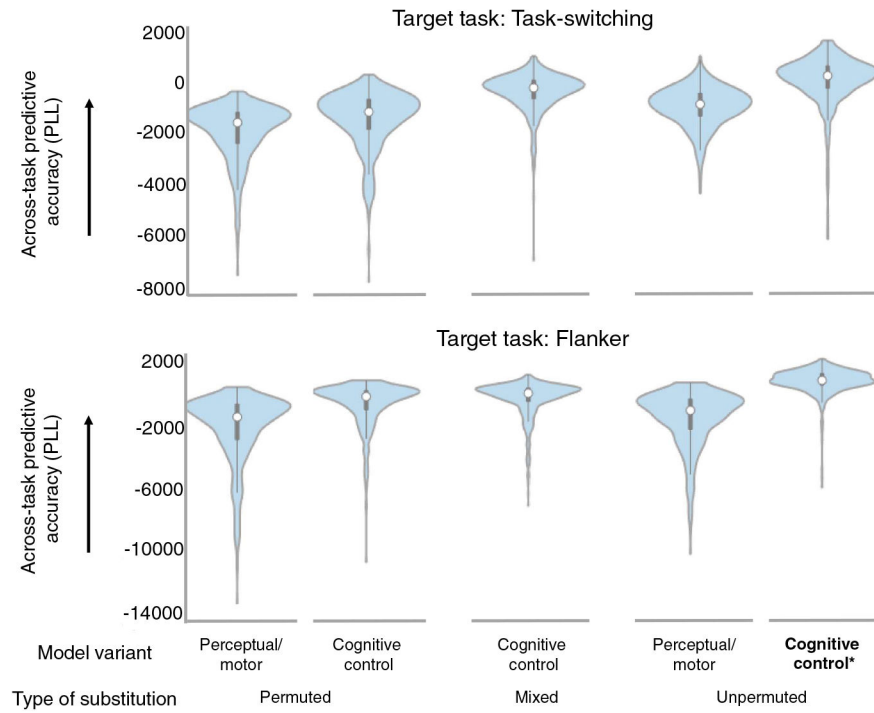
Figure 7. Predictive Accuracy from Across-Task Parameter Substitution
Note. Violin plots of individual users' predictive log likelihood (PLL) for each way of substituting parameters (i.e., permuted, mixed and unpermuted) and each variant of the task model (perceptual/motor and cognitive control). Higher values of the PLL indicate higher predictive accuracy. Asterisk marks the best performing substitution and model variant. Both when predicting task-switching and flanker data, we found that predictive accuracy was highest for unpermuted substitution with the full cognitive control model. This provides converging support for the view that cognitive control processes are shared across these two tasks.