Incentive Effects Capture Variability in Task-General Control Allocation

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Abstract

To understand how people vary in their cognitive control engagement, researchers use different laboratory tasks and compare performance on trials that are more versus less control-demanding (e.g., congruency effects). However, previous research has struggled to uncover consistent patterns of correlation across cognitive control tasks, leading to questions about the utility of these tasks and the existence of task-general control. The current study sought to test whether these validity concerns may center on the stimulus-driven nature of congruency effects, rather than the tasks themselves. To overcome this obstacle, we varied task incentives while holding stimulus features constant. We show both theoretically and empirically that the effects of incentives on control allocation correlate across tasks. Together, findings support task-general control processes that operate across different contexts.

Keywords: cognitive control; motivation; computational modeling, response conflict

Introduction

Cognitive control refers to the set of mechanisms required to pursue goals, by adapting mental processes and behavior to situational demands (Braver, 2012; Shenhav et al., 2013; Braem & Egner, 2018). Effective engagement of cognitive control is critical for overcoming distractions and guiding behavior toward desired outcomes. Thus, understanding individual differences in cognitive control engagement is relevant and important for diverse research areas such as education, aging, neurodevelopmental disorders, and psychiatric disorders (Diamond et al., 2007; Erb et al., 2023; Liu et al., 2018; Paulus, 2015).

To assess variability in the capacity to engage cognitive control across individuals, researchers often examine how performance varies as a function of the degree to which goal-irrelevant information interferes (conflicts) with goal-relevant information (Egner, 2008). When these elements are incongruent with one another, it is believed that more control is demanded to respond to the goal-relevant information; when these features are congruent with one another, there is less of a demand for control. Congruency is often manipulated by altering stimulus features like word color, stimulus direction, and response direction (Simon, 1969; Stroop, 1935; Eriksen & Eriksen, 1974). By contrasting performance (accuracy and response time) on incongruent versus congruent trials, researchers obtain a metric referred to as the *congruency effect*, which they use to evaluate cognitive control engagement across paradigms. Specifically, smaller congruency effects are interpreted as evidence that greater control is being allocated (the impact of which is to reduce interference from distractors). By the same token, individuals who demonstrate smaller congruency effects are seen as generally exerting greater control, potentially reflecting a greater capacity for control (i.e., better cognitive ability).

However, questions have arisen regarding the construct and convergent validity of congruency effects. If congruency effects reflect stable, person-level cognitive control abilities, these effects should show consistent correlations across various laboratory tasks, and align with real-life self-control successes. In other words, if congruency effects tap into a common underlying process (i.e., levels of cognitive control invested), individuals who struggle to inhibit irrelevant features in one task should also exhibit larger congruency effects in another task and poorer self-control in real-world scenarios. Contrary to this prediction, though, numerous studies have reported weak to null associations between congruency effects across diverse established tasks (e.g., Shilling et al., 2002; Rouder & Haaf, 2019; Rey-Mermet et al., 2018). Moreover, congruency effects fail to correlate with measures of self-control in daily life (Saunders et al., 2017; Paap et al., 2020).

Collectively, these findings challenge the assumption that congruency effects capture task-general adjustments in cognitive control. They have also raised concerns about the validity of laboratory-based measures of cognitive control more generally (Paap et al., 2020). To reconcile this, some have argued that the mechanisms underlying cognitive control may be task-specific and different tasks may rely on different control processes (Whitehead et al., 2020; Rey-Mermet & Suisse, 2024). If this is the case, performance scores from one task should not be broadly interpreted as indicators of cognitive control without evidence to support the existence of task-general control signals or correlation between performance scores in these tasks.

An alternative explanation for this absence of inter-task correlations is that it reflects deficiencies in the performance metric being examined (congruency effects), rather than in

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the tasks themselves. Specifically, since congruency effects in part reflect stimulus-driven factors (e.g., the strength of learned associations between features and responses), it has been proposed that individual differences in congruency effects may to a large degree reflect individual differences in the automaticity of task-specific feature processing instead of (or in addition to) control allocation (Musslick et al., 2019). If this is the case, distinct cognitive tasks may in fact recruit common control processes, but congruency effects would fail to capture these control processes because they primarily reflect stimulus-driven processes.

Prior studies have provided evidence that the motivation to apply top-down control influences cognitive control allocation (Shenhav et al., 2013; Musslick et al., 2015). Many studies have observed incentive-induced performance improvements in cognitive control tasks (e.g., Padmala & Pessoa, 2011; Chiew & Braver 2014; Savine et al., 2010; Leng et al., 2021). Therefore, motivational manipulations may offer unique opportunities to disentangle the stimulus-driven processes and validly examine the existence of task-general control in distinct cognitive tasks. Notably, within-participant manipulations of reward or penalty motivations would hold bottom-up processes constant, and the performance difference when the participant is motivated by high vs. low incentive can be more purely attributed to top-down control allocation (Figure 1). Thus, if motivational effects on performance are found to be correlated across tasks, this would support the existence of task-general control processes that operate across different contexts. In contrast, if different cognitive control tasks rely on distinct control processes and incentive-induced motivation promotes the task-specific cognitive control, we would not expect the effects of motivation on control engagement to correlate across tasks.

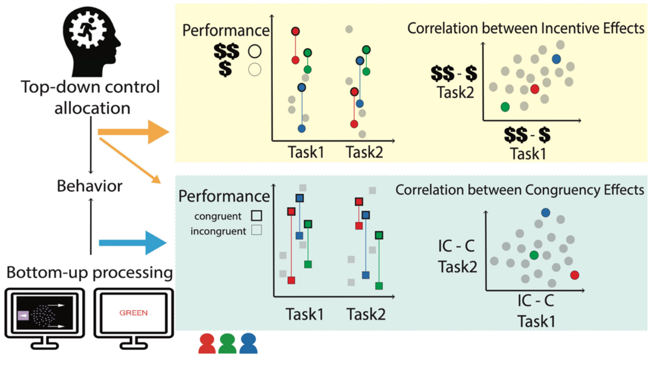

Figure 1: Illustration of study predictions. A combination of top-down control allocation and bottom-up stimulus processing drive task performance. Congruency effects can be driven by both processes. Therefore, a lack of correlation between congruency effects may be driven by the differences in bottom-up processes across tasks, instead of the lack of a domain-general, top-down control allocation. In contrast, incentive effects are mainly driven by top-down control allocation and if task-general control allocation exist, incentive effects should be stable across tasks.

To more rigorously examine whether task-general control exists and whether previous validity concerns may center on the metrics rather than the tasks, the current study orthogonally manipulated congruency and incentives in two cognitive control tasks. We conducted simulation and empirical investigations on the strength of correlation between the congruency and incentive effects across tasks. We predicted that the incentive effects (which are not confounded with bottom-up processes and reflect top-down control allocation) would correlate better than congruency effects. Empirical support for our hypothesis would provide evidence for task-general control processes that are detectable from laboratory cognitive control tasks and highlight the need for developing valid indices of top-down cognitive control in lab-based tasks.

Methodology – Experimental Tasks

We examined variability in performance on two cognitive control tasks. One of these was the Stroop task, where participants need to overcome the automaticity of reading words and identify the font color (Stroop, 1935). The other was a Random Dot Motion variant of the Simon task (RDM-Simon), where participants need to respond with a left or right button press depending on the color of the dots, while ignoring the direction of dot motion, which could be congruent or incongruent with the correct response (Danielmeier et al., 2011; Ritz & Shenhav, 2024). Each task was broken up into four blocks, each consisting of 12 turns. Within each turn, participants were given a window of time (~7s) within which they could complete as many trials as they wanted and were able. Critically, this task explicitly orthogonalized the impact of incentives and task demands on performance, by independently varying congruency (incongruent or congruent), reward per correct response ($0.01 or $0.10), and penalty per incorrect response ($0.01 or $0.10). This enabled us to disentangle stimulus-driven influences on performance (e.g., congruency-related) from top-down influences (e.g., incentive-related), thus systematically investigating the generalizability of each metric across tasks.

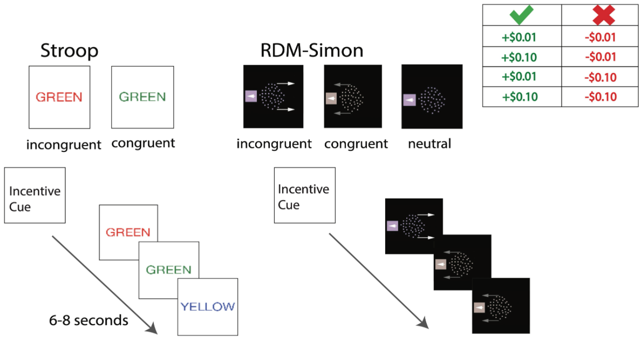

Figure 2: Interval-based multi-incentive cognitive control tasks. At the start of each interval, a visual cue indicates the amount of reward (monetary gain) for correct responses and the penalty (monetary loss) for incorrect responses within

that interval. Participants can complete as many trials as they wish within an interval. Each participant completed two cognitive control tasks (Stroop and Random Dot Motion variant of the Simon task) under the same incentivized design and with 50% proportion congruency.

Simulation Framework

To capture the influence of both stimulus-driven and top-down factors in determining task performance, we simulated control allocation and resulting behavior based on the expected value of control (EVC) theory (Shenhav et al., 2013; Musslick et al., 2015), factoring in the trial-level influence of task automaticity, expected reward for good performance, expected penalty for bad performance, and cost for implementing control.

In the simulation, each cognitive control task involves a goal-relevant feature (e.g., ink color) and a goal-irrelevant feature (e.g., word form). To simulate response time (RT) and accuracy, we used the drift diffusion model (DDM) and formalized task responses as evidence accumulation towards the responses (respond to target vs. respond to distractor). In the model, drift rate towards one of the responses is determined by the automatic and controlled processing of the task components:

$$drift = drift_{automatic} + drift_{control}$$
$$drift_{automatic} = a_{distractor} + a_{target}$$
$$drift_{control} = (a_{distractor} * u_{distractor} + a_{target} * u_{target}) * \varepsilon$$

The magnitudes of $a_{target}, a_{distractor}$ indicates the automaticity of the task dimensions and we kept $|a_{target}| < |a_{distractor}|$. The a_{target} and $a_{distractor}$ have the same sign (i.e., both positive) on congruent trials such that the automatic drift rate is towards the target response. $a_{distractor} < 0$ on incongruent trials such that the automatic drift rate is towards the distractor response. The u_{target} and $u_{distractor}$ capture the intensity of (task-general) top-down control applied to each feature, and ε captures the efficiency of control allocation (a proxy for control capacity).

On each trial t, the model estimates the optimal set of control signals (U includes $u_{target}, u_{distractor}$, and decision threshold A) based on its inferred task state $\hat{S}$ to maximize the expected value of control:

$$EVC\ (U, \hat{S}\ ) = \frac{P_{upper}(U,\hat{S}\ ) * R_{rew} * \text{Reward} - P_{lower}(U,\hat{S}\ ) * R_{pen} * \text{Penalty}}{dt\ (U,\hat{S}) + ndt} - \text{Cost}(\text{U}, \hat{S})$$

$$U^{*} \text{<- argmax}\ [EVC\ (U, \hat{S}\ )]$$

Given the control signal and inferred task state (U and $\hat{S}$), P_{upper}, P_{lower}, and dt were calculated from an analytical solution of the DDM (Navarro and Fuss, 2009). We modeled control reconfiguration costs by simulating adjustments from one's previous control state U_{t-1}^{*} to the target state U_{t}^{*} as a dynamic process with inertia (Grahek et al., 2023). The implementation cost of the control signal was calculated based on an exponential function:

$$\text{Cost}(\text{U}, \hat{S}) = e^{C * u_{target}} + e^{C * u_{distractor}} + e^{C * A}$$

We simulated N=50 agents performing these tasks, with agents varying in their incentive sensitivities ($R_{rew}, R_{pen} \in$ [0.6, 1]), control costs ($C \in [1, 1.5]$), and control capacity ($\varepsilon \in$ [1, 2]). The automaticity of the distractor and target components also varied within an agent across tasks ($|a_{distractor}| \in$ [0.4, 0.5]; $|a_{target}| \in$ [0.2, 0.4]).

Simulation Results

Analyses of Task Performance

To understand the effects of task variables (response congruency, expected reward, and expected penalty) on the task performance for these simulated agents, we used linear mixed models to analyze RT and accuracy in each task (lme4 in R; Bates et al., 2015). These regressions revealed that behavior of these agents recapitulated patterns observed in prior research (e.g., Leng et al., 2021; Prater Fahey et al., 2025), such that simulated agents performing both tasks were faster and more accurate for congruent trials; faster and more accurate for larger rewards; and slower and more accurate for larger penalties (ps < .01; Table 1).

Analyses of Task-General Control

To examine the generality of performance metrics across tasks, for each agent and task we calculated the effects of congruency, expected reward, and expected penalty on their performance. We then examined the extent to which variability in each of these metrics (e.g., the effect of congruency on RT) was correlated across the two tasks.

Results revealed that the effect of rewards in promoting faster and more accurate responses was correlated across tasks, as was the effect of penalties in promoting slower and more accurate responses (rs > .40; ps < .01). Therefore, agents who increased control allocation in response to potential incentives in one task, also exhibit similar levels of increased control allocation in another task. In contrast, congruency effect on accuracy or RT did not correlate across tasks (ps > .10) (Table 1).

The simulation findings demonstrated that in an environment where control is allocated in a task-general manner (i.e., with the same U optimized across these two tasks), incentive-related performance metrics are effective in capturing commonalities in control allocation across tasks. To validate these predictions, we next examine the extent to which these predicted cross-task correlations are observed empirically.

Table 1: Congruency, reward, and penalty effects on simulated task performance.

Predictor	*Behavior*	*Effect Size Task 1*	*Effect Size Task 2*	***Cross-task Corr(r)***
congruency	RT	-0.20***	-0.16***	**0.22**
	Accuracy	0.39***	0.40***	**0.18**
reward	RT	-0.34***	-0.30***	**0.45****
	Accuracy	0.30***	0.28***	**0.53*****
penalty	RT	0.08**	0.11**	**0.41****
	Accuracy	0.19***	0.17***	**0.45*****
				* p< .05 ** p< .01 *** p< .001

Empirical Results

Analyses of Task Performance

A total of 106 participants completed the Stroop and RDM-Simon tasks in randomized orders via Prolific. As in our theoretical analyses, we applied linear mixed models to analyze RT and accuracy in each task. Results revealed that responses in both tasks were faster and more accurate for congruent trials; faster for larger rewards; and slower and more accurate for larger penalties (Figure 3A; ps < .001).

To decompose the dynamics underlying task performance, we fit these behavioral data to a DDM. The effects of stimulus-congruency, expected reward, and expected penalty on the DDM parameters were estimated using a hierarchical Bayesian framework implemented in the HDDM package (Wiecki et al., 2013). The drift diffusion model distinguished between distinct control processes (drift rate, threshold) influenced by the different incentives. Consistent with normative predictions and empirical findings (Bogacz et al., 2006; Leng et al., 2021), when motivated by rewards, participants prioritized speed by decreasing decision threshold (requiring less evidence before responding; p < .001). When motivated by penalties, participants prioritized accuracy by increasing both threshold and drift rate (ps < .001). Also consistent with previous findings, participants demonstrated lower drift rates and a starting point bias towards the distractor-related response on incongruent relative to congruent trials (ps < .001)(Figure 4A).

Analyses of Task-General Control

To estimate cross-task correlations in these empirically observed performance metrics, we calculated individual-level effects of congruency, expected reward, and expected penalty on performance (RT and starting accuracy) and decision parameters (drift rate, threshold, and point bias). These effects quantified the modulation of task variables on control adjustments for each individual and task.

Using robust regressions, we next tested whether the influence of a given task variable (e.g., potential reward) on performance on one task (e.g., Stroop) correlated with the influence of that variable on performance on the other task (e.g., RDM-Simon). Our model-agnostic analyses revealed that this was the case both for the effect of reward on promoting faster responses (B = 0.37, p < .001), as well as the effect of penalty on promoting slower responses (B = 0.22, p = 0.01). In contrast, we found no such inter-task correlations for the effect of congruency on speed or accuracy (ps > .45)(Figure 3B).

Our model-based analyses revealed cross-task correlations between the effect of reward on decreasing decision threshold (B = 0.35, p <.001), as well as the effect of penalty on increasing decision threshold (B = 0.36, p <.001). Cross-task correlations for congruency effects were weaker and/or only trending (starting point bias: B = 0.23, p =0.002; drift rate: B = 0.16, p = 0.12).

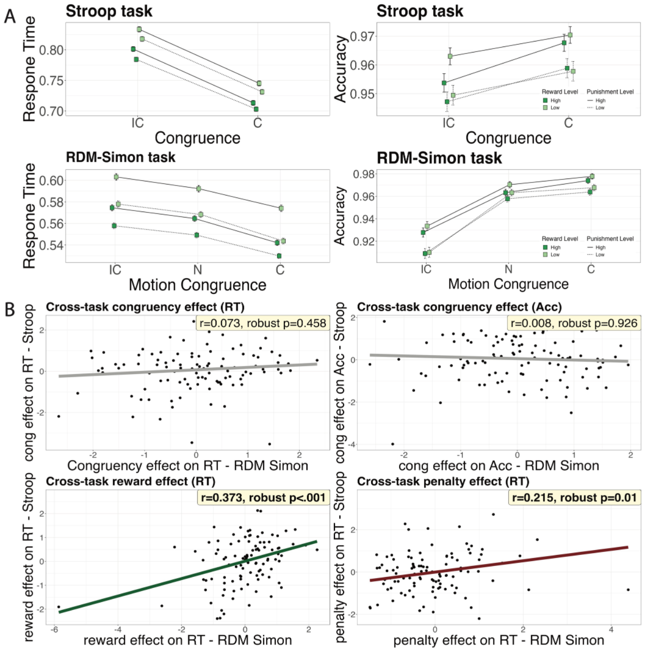

Figure 3. Effects of congruency, reward, and penalty on overall task performance[1]. (A) In both tasks, task performance improved when congruency, reward, or penalty was high. (B) Reward and penalty effects on RT correlated between the tasks, while congruency effects on RT or accuracy did not.

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[1] Note that the correlation coefficients were estimated from robust regressions. The correlations between reward and penalty effects on RT persisted (rs > .20, ps < .05) after outlier removal.

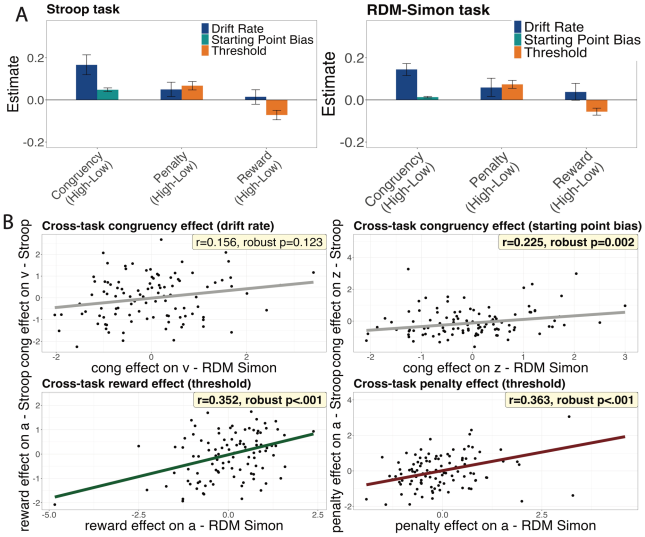

Figure 4. Effects of congruency, reward, and penalty on DDM parameters. (A) The effects of task variables on the decision dynamics were similar across tasks. (B) Reward and penalty effects on threshold correlated between task, while congruency effects showed either weak (starting point) or no (drift) correlation.

Discussion

Challenges in linking performance metrics, such as congruency effects, across laboratory cognitive tasks have raised concerns that different tasks may engage task-specific rather than task-general control processes. To provide a stronger test of task-general control mechanisms, we investigated the role of motivational variables—specifically rewards and penalties—in modulating cognitive performance across different tasks. Our results accord with previous observations that congruency effects are weakly correlated across tasks, while at the same time showing that these weak correlations reflect limitations of the task manipulation (congruency) rather than the task itself. We show that, unlike congruency effects, the effects of incentives (reward or penalty) on performance consistently generalize across tasks. The findings provide evidence for task-general control mechanisms and suggest that capturing such task-general control requires measuring changes in performance that can be more directly ascribed to top-down control.

These findings contribute to ongoing debates about whether domain-general or domain-specific control processes underlie performance across different cognitive control tasks. Previous research that failed to identify correlations among classic cognitive control tasks (e.g., Stroop, Flanker, Simon) has proposed two primary explanations. Some researchers argue that performance in each task is determined by highly specific task-related abilities rather than shared control processes, suggesting that these tasks are valid only as measures of distinct cognitive control mechanisms (Rey-Mermet et al., 2018). Others suggest that these tasks predominantly reflect general information processing speed rather than higher-order cognitive abilities, thereby limiting their utility for assessing domain-general cognitive control mechanisms (Jewsbury et al., 2016; Löffler et al., 2024). In this study, we addressed prior limitations by holding stimulus-driven processes constant within each task while allowing participants to engage in varying levels of control intensity in response to varying incentives. By examining the correlation between variations in control intensity across tasks—while controlling for baseline speed and accuracy—we found evidence that incentives modulate control intensity along a shared axis, independent of task contexts. These findings support the existence of a task-general cognitive control that can be effectively measured by focusing on the dynamics of top-down control allocation.

Our findings also have important implications for using cognitive control tasks as tools to index control intensity. Specifically, the absence of correlations between traditional performance metrics across laboratory control tasks should not be misinterpreted as evidence against task-general control processes. Instead, it reflects the limitations of certain task metrics. Cognitive control is conceptualized as the top-down mechanisms that allow individuals to maintain goal-directed thoughts or actions under changing demands and contexts (Braver, 2012; Shenhav et al., 2021). However, commonly used performance metrics, such as congruency effects, are often sensitive to low-level task features—such as task automaticity—that do not adequately capture the higher-order processes involved in goal-directed control allocation. Therefore, these metrics may not quantify the intended construct of cognitive control effectively. Our simulated and experimental findings highlight that overall engagement of control can be jointly determined by various factors (e.g., stimulus-response associations, control capacity, motivation). Together, our findings have further practical implications on assessments of cognitive control. For example, the NIH Toolbox includes congruency effects from the Flanker task as a measure of inhibitory control that carry significance in diverse research areas such as human development or psychiatric disorders (Weintraub et al., 2013). However, our results demonstrate that the stimulus-driven nature of congruency effect limits its construct validity in assessing task-general control mechanisms, and that task manipulations targeting top-down control allocation provide a more accurate representation of the underlying construct.

The current study utilized a specific set of cognitive control tasks to provide both theoretical and experimental evidence supporting the generalizability of control adjustments across contexts. Future studies may expand on these findings and examine cross-task correlations in incentive effects in the context of a broader range of task paradigms with diverse cognitive demands (e.g., task-switching, working memory). Future studies may also investigate potential moderators between motivation and control allocation (e.g., task difficulty) to investigate the consistency or boundary conditions of detectable task-general control.

In conclusion, this study provides evidence for task-general control processes involved in different cognitive control tasks. These findings emphasize the need for refined metrics and models of cognitive control that can effectively capture variability in control allocation across tasks and individuals.

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References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Braem, S., & Egner, T. (2018). Getting a grip on cognitive flexibility. *Current directions in psychological science*, *27*(6), 470-476.

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological review*, *113*(4), 700.

Braver, T. S. (2012). The variable nature of cognitive control: a dual mechanisms framework. *Trends in cognitive sciences*, *16*(2), 106-113.

Chiew, K. S., & Braver, T. S. (2014). Dissociable influences of reward motivation and positive emotion on cognitive control. *Cognitive, Affective, & Behavioral Neuroscience*, *14*, 509-529.

Danielmeier, C., Eichele, T., Forstmann, B. U., Tittgemeyer, M., & Ullsperger, M. (2011). Posterior medial frontal cortex activity predicts post-error adaptations in task-related visual and motor areas. *Journal of Neuroscience*, *31*(5), 1780-1789.

Diamond, A., Barnett, W. S., Thomas, J., & Munro, S. (2007). Preschool program improves cognitive control. *Science*, *318*(5855), 1387-1388.

Egner, T. (2008). Multiple conflict-driven control mechanisms in the human brain. *Trends in cognitive sciences*, *12*(10), 374-380.

Erb, C. D., Germine, L., & Hartshorne, J. K. (2023). Cognitive control across the lifespan: Congruency effects reveal divergent developmental trajectories. *Journal of Experimental Psychology: General*.

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & psychophysics*, *16*(1), 143-149.

Fahey, M. P., Yee, D. M., Leng, X., Tarlow, M., & Shenhav, A. (2025). Motivational context determines the impact of aversive outcomes on mental effort allocation. *Cognition*, *254*, 105973.

Grahek, I., Leng, X., Musslick, S., & Shenhav, A. (2023). Control adjustment costs limit goal flexibility: Empirical evidence and a theoretical account. *bioRxiv*, 2023-08.

Jewsbury, P. A., Bowden, S. C., & Strauss, M. E. (2016). Integrating the switching, inhibition, and updating model of executive function with the Cattell—Horn—Carroll model. *Journal of Experimental Psychology: General*, *145*(2), 220.

Leng, X., Yee, D., Ritz, H., & Shenhav, A. (2021). Dissociable influences of reward and punishment on adaptive cognitive control. *PLoS computational biology*, *17*(12), e1009737.

Liu, X., Liu, T., Shangguan, F., Sørensen, T. A., Liu, Q., & Shi, J. (2018). Neurodevelopment of conflict adaptation: Evidence from event-related potentials. *Developmental Psychology*, *54*(7), 1347.

Löffler, C., Frischkorn, G. T., Hagemann, D., Sadus, K., & Schubert, A. L. (2024). The common factor of executive functions measures nothing but speed of information uptake. *Psychological research*, 1-23.

Musslick, S., Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2015, June). A computational model of control allocation based on the expected value of control. In *Reinforcement Learning and Decision Making Conference* (Vol. 2015).

Musslick, S., Cohen, J. D., & Shenhav, A. (2019). Decomposing Individual Differences in Cognitive Control: A Model-Based Approach. In *CogSci* (pp. 2427-2433).

Paulus, M. P. (2015). Cognitive control in depression and anxiety: out of control?. *Current Opinion in Behavioral Sciences*, *1*, 113-120.

Paap, K. R., Anders-Jefferson, R., Zimiga, B., Mason, L., & Mikulinsky, R. (2020). Interference scores have inadequate concurrent and convergent validity: Should we stop using the flanker, Simon, and spatial Stroop tasks?. *Cognitive research: principles and implications*, *5*, 1-27.

Padmala, S., & Pessoa, L. (2011). Reward reduces conflict by enhancing attentional control and biasing visual cortical processing. *Journal of cognitive neuroscience*, *23*(11), 3419-3432.

Rey-Mermet, A., Gade, M., & Oberauer, K. (2018). Should we stop thinking about inhibition? Searching for individual and age differences in inhibition ability. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(4), 501.

Rey-Mermet, A., & Suisse, U. (2024). Beyond Unity and Diversity: Tasks Used to Assess Attentional Control Measure Task-Specific Processes.

Ritz, H., & Shenhav, A. (2024). Humans reconfigure target and distractor processing to address distinct task demands. *Psychological review*, *131*(2), 349.

Rouder, J. N., & Haaf, J. M. (2019). A psychometrics of individual differences in experimental tasks. *Psychonomic bulletin & review*, *26*(2), 452-467.

Savine, A. C., Beck, S. M., Edwards, B. G., Chiew, K. S., & Braver, T. S. (2010). Enhancement of cognitive control by approach and avoidance motivational states. *Cognition and Emotion*, *24*(2), 338-356.

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron*, *79*(2), 217-240.

Shenhav, A., Prater Fahey, M., & Grahek, I. (2021). Decomposing the motivation to exert mental effort. *Current directions in psychological science*, *30*(4), 307-314.

Shilling, V. M., Chetwynd, A., & Rabbitt, P. M. A. (2002). Individual inconsistency across measures of inhibition: An investigation of the construct validity of inhibition in older adults. *Neuropsychologia*, *40*(6), 605-619.

Simon, J. R. (1969). Reactions toward the source of stimulation. *Journal of experimental psychology*, *81*(1), 174.

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of experimental psychology*, *18*(6), 643.

Weintraub, S., Dikmen, S. S., Heaton, R. K., Tulsky, D. S., Zelazo, P. D., Bauer, P. J., Carlozzi, N. E., Slotkin, J., Blitz, D., Wallner-Allen, K., Fox, N. A., Beaumont, J. L., Mungas, D., Nowinski, C. J., Richler, J., Deocampo, J. A., Anderson, J. E., Manly, J. J., Borosh, B., Havlik, R., … Gershon, R. C. (2013). Cognition assessment using the NIH Toolbox. *Neurology*, *80*(11 Suppl 3), S54–S64.

Whitehead, P. S., Brewer, G. A., & Blais, C. (2020). Reliability and convergence of conflict effects. *Experimental Psychology*.

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python. *Frontiers in neuroinformatics*, *7*, 55610.