Inhibition and Updating Share Common Resources: Bayesian Evidence from Signal Detection Theory and Drift Diffusion Model

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Abstract

Inhibition and updating are fundamental cognitive functions in humans, yet the nature of their relationship—whether shared or distinct—remains ambiguous. This study investigates the relationship between inhibition and updating within a unified task framework using a novel paradigm that integrates the N-back task with the congruent/incongruent Stroop task, creating conditions that require either updating alone or both inhibition and updating. Employing Signal Detection Theory (SDT) and the hierarchical drift diffusion model (HDDM), the results provided overall extremely strong Bayesian evidence that participants exhibited longer response times and lower accuracy in conditions requiring both inhibition and updating, compared to those requiring only updating. SDT analysis revealed a decline in discriminability, while HDDM analysis showed slower drift rates, longer non-decision times and a lower decision threshold in inhibition-demanding conditions. Even after controlling for the congruency sequence effect and current stimulus attributes, the results remained robust, showing a larger inhibition effect size compared to the traditional Stroop task. These findings suggest that inhibition consumes cognitive resources, impairing updating performance, and implying that both functions may rely on shared cognitive resources. Overall, the results elucidate the relationship between these fundamental executive functions, supporting the notion that inhibition and updating share cognitive resources.

Keywords: inhibition, updating, executive function, drift diffusion model, congruency sequence effect

1. Introduction

In the contemporary era of information abundance, knowledge acquisition is frequently impeded by irrelevant information. Consequently, it is imperative for individuals to inhibit distractions and effectively update their knowledge. Inhibition refers to the ability to overcome automatic behaviors or interference from irrelevant information to achieve a goal (Baddeley, 1996; Diamond, 2013; Miyake et al., 2000). Updating involves the ability to receive and temporarily store information, including monitoring, adding, and deleting contents from working memory (Holder et al., 2021). While previous research has suggested that inhibition and updating are distinct components of executive function (Diamond, 2013; Espy, 2004), emerging evidence reveals correlations between performance on inhibition and updating tasks (Collette et al., 2005; Engelhardt et al., 2015; Fleming et al., 2016; Friedman et al., 2008, 2011; Ito et al., 2015; Niendam et al., 2012; Saylik et al., 2022). Thus, the relationship between inhibition and updating remains ambiguous.

The debate on whether inhibition and updating are distinct functions or share common resources persists (Jurado & Rosselli, 2007; Miyake et al., 2000). Research supporting their distinction suggested that a single-factor model combining these three executive functions (inhibition, updating, and shifting) did not fit the data as well as a three-factor model with separate components, indicating that inhibition and updating are separate processes (Miyake et al., 2000). Expanding on this, further research revealed that inhibition is more closely related to processing speed, whereas updating is predominantly linked to short-term memory capacity (Jewsbury et al., 2016). Besides, neuropsychological findings provide additional support for this dissociation. Patients with different damaged brain regions showed divergent performances in working memory and inhibition tasks, implying that these functions may be governed by different neural substrates (Godefroy et al., 1999). Saylik et al. (2022) further identified specific particular brain regions for inhibition and updating: the left inferior frontal gyrus for inhibition, the bilateral middle frontal gyrus, and the left supramarginal gyrus for updating. Conversely, other evidence suggested that inhibition and updating may share common cognitive resources. For instance, Friedman et al. (2011) employed a set of independent tasks to measure inhibition and updating, revealing that inhibition and updating could be integrated into a single “Common Executive Function Factor” through latent variable analysis. More recently, large-sample studies have further supported this shared relationship (Freis et al., 2022, 2024). Consistent with this view, neuroimaging research has identified the prefrontal cortex (PFC) as a common neural substrate for inhibition and updating

(Niendam et al., 2012). Despite extensive exploration, the relationship between inhibition and updating remains inconclusive.

A key reason for this ongoing debate is that researchers often measure inhibition and updating functions separately rather than concurrently. For instance, Saylik et al. (2022) used the Stroop task (Stroop, 1935) to measure inhibition and the N-back task to measure updating. Similarly, Friedman et al. (2011) used various tasks to assess inhibition and updating independently (Engelhardt et al., 2015; Fleming et al., 2016; Friedman et al., 2008, 2011; Ito et al., 2015). These traditional research approaches lack paradigms that can concurrently assess both inhibition and updating, emphasizing the need for novel experimental designs to explore their concurrent processing.

Another factor contributing to the ongoing debate is that different measurement indicators were used in inhibition and updating tasks (Von Bastian et al., 2020). Experiments often use reaction time as an indicator of inhibition and accuracy as an indicator for updating (Del Missier et al., 2010; Fleming et al., 2016; Friedman et al., 2008; Himi et al., 2019, 2021; Martins et al., 2018). A meta-analysis demonstrated that most inhibition tasks rely on either reaction time or accuracy as the sole measurement indicator, while updating tasks typically use accuracy as the primary indicator (Von Bastian et al. 2020). This discrepancy in measurement indicators reflects the distinct methods used to assess each function: inhibition tasks often use subtraction methods, while updating tasks typically use average performance (Del Missier et al., 2010; Smolker et al., 2018). Relying on a single measurement indicator poses challenges, as even within the same task, the correlation between reaction time and accuracy is low, and results vary significantly across tasks (mean r = .17, range = .45 to .78; Wiecki et al., 2018). This suggests that individual differences in speed-accuracy trade-offs affect the overall distribution of reaction time and accuracy. The speed-accuracy trade-off refers to the phenomenon where prioritizing one dimension (speed or accuracy) typically compromises the other (Heitz, 2014). Numerous studies have shown that reaction time is highly sensitive to speed-accuracy trade-offs (Draheim et al., 2019). Although researchers attempt to balance participants' speed-accuracy trade-offs through instructions, participants still tend to adopt different response strategies based on their personal priorities (Draheim et al., 2021; Heitz, 2014). Additionally, individuals may adjust their speed-accuracy trade-offs to meet the demands of specific tasks (Draheim et al., 2016). Furthermore, studies have found that speed-accuracy trade-offs also occur in paradigms that solely measure accuracy (Hedge et al., 2018, 2022). Collectively, this body of evidence suggests that using a single measurement indicator is susceptible to individual speed-accuracy trade-offs,

potentially distorting results. Therefore, relying on a single task with a single measurement indicator to assess specific executive functions and analyze their correlations may not accurately reflect their true relationship.

To overcome the limitation that previous studies typically measured inhibition and updating separately using different tasks, we first developed an innovative stimulus-task incompatibility experimental paradigm that enables their concurrent processing. This paradigm integrates the N-back task with the congruent/incongruent Stroop task. The N-back task requires participants to continuously judge whether the current stimulus matches the previous one (**Figure 1.A)**, thereby engaging updating (Colom et al., 2008; Hockey & Geffen, 2004; Redick & Lindsey, 2013). The congruent/incongruent Stroop task, which requires participants to classify stimuli based on whether the word's color and semantic meaning are congruent or incongruent **(Figure 1.B)**, does not require participants to inhibit their automatic response to word meaning and therefore differs from the traditional Stroop task (Mager et al., 2007; Zurrón et al., 2009). In our study, participants were asked to judge whether the color-word congruency of the current Chinese character matched the color-word congruency of the previous one (**Figure 1.C**). This task created two critical conditions: one requiring both inhibition and updating, and the other requiring only updating. These conditions were determined by the color-word congruency of the previous trial. In both inhibition and updating required condition (when the color-word congruency of the previous trial is incongruent, e.g., ii, where the color-word congruency of both previous and current trials is incongruent; ic, where the color-word congruency of previous trial is incongruent, while current trial is congruent), inhibition was necessary to resolve the conflict between bottom-up, stimulus-driven processing (evaluating the color-word congruency of the current stimulus) and top-down, task-driven processing (determining whether the color-word congruency of the current stimulus matches the previous one). This conflict resulted in stimulus-task incompatibility, requiring participants to inhibit bottom-up processing of the stimulus attribute to successfully execute the top-down task-related judgment. In the only updating required condition (when the color-word congruency of the previous trial is congruent, e.g., cc, where the color-word congruency of both previous and current trials is congruent; ci, where the color-word congruency of previous trial is congruent while current trial is incongruent), the bottom-up stimulus-driven processing and the top-down task-driven processing were aligned, resulting in stimulus-task compatibility. In this condition, participants could complete the updating task without inhibiting the stimulus-driven processing. Thus, our task includes conditions that require both inhibition and updating, as well as conditions that require only updating, allowing for the concurrent measurement of inhibition and updating within a unified task framework. The key assumption underlying this

paradigm is that if inhibition impairs updating performance, it would indicate that inhibition and updating rely on shared cognitive resources.

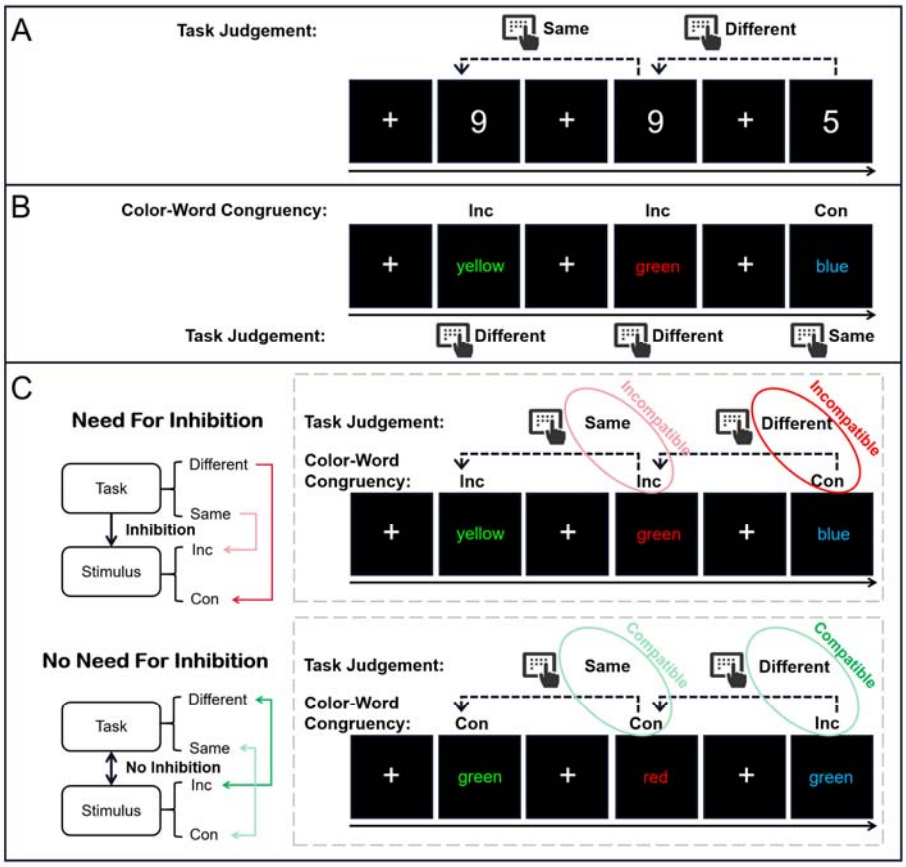


Figure 1. Flowchart of the Traditional N-back Task, Congruent/Incongruent Stroop Task, and Our Novel Task. (A) Traditional N-back (one-back) task. Participants are required to determine whether the current stimulus matches the previous one. (B) Traditional congruent/incongruent Stroop task. Participants are required to judge whether the current stimulus color-word congruency is congruent (same) or incongruent (different). (C) Our novel task. In each trial, a colored Chinese character is presented (For illustration, we show the English version instead of the Chinese characters). The congruency of the color and its meaning can be either congruent or incongruent. Participants are instructed to judge whether the color-word congruency of the current stimulus matches that of the previous trial. This paradigm leverages the color-word congruency of the previous stimulus to induce stimulus-task incompatibility: When the color-word congruency of the previous stimulus was incongruent (upper panel), color-word congruency of the current stimulus conflicts with the task judgement, necessitating inhibition. When the color-

word congruency of the previous stimulus was congruent (lower panel), color-word congruency of the current stimulus aligns with the task judgement, only need updating.

However, our task may be influenced by inhibition-related factors. The Congruency Sequence Effect (CSE), also known as the "Gratton effect", refers to the phenomenon where the congruency effect is reduced following inhibition-required trials compared to non-inhibition-required trials (Duthoo et al., 2014; Egner, 2007). Previous studies have shown that CSE commonly occurs in tasks requiring inhibition (Braem et al., 2019; Frings et al., 2020). Therefore, to examine and minimize the potential impact of CSE on our results, we also considered the stimulus-task compatibility of the previous trial (i.e., whether inhibition was required in the previous trial).

Furthermore, to overcome the limitation of using different indicators for inhibition and updating, this study employs Signal Detection Theory (SDT) and the hierarchical drift diffusion model (HDDM) to analyze the computational mechanisms underlying the relationship between inhibition and updating. For the N-back task, SDT is frequently utilized to evaluate updating capability. SDT analysis (Maniscalco & Lau, 2014; Stanislaw & Todorov, 1999) is a method that separately quantifies discriminability and bias through accuracy metrics. It provides a comprehensive framework for understanding how decision-makers pool information based on sensory stimuli in a bottom-up manner or how top-down information influences decisions (Green & Swets, 1966). This framework can explore whether top-down inhibition impacts updating discriminability (i.e., the discriminability index d') and how the bias (i.e., decision bias c) to classify a stimulus as a target (or non-target) shifts under equal uncertainty conditions. A higher d' shows an enhanced ability to discern if the current stimulus matches the previous one, whereas decision bias (c) can be interpreted as liberal ($c < 0$), neutral ($c = 0$), or cautious ($c > 0$) (Dawkins et al., 2007). If inhibition and updating share cognitive resources, simultaneous inhibition and updating should result in lower discriminability (d') compared to scenarios where only updating is required, while decision bias (c) should remain neutral since the task does not involve probabilistic learning and the number of response keys is equally controlled, with decision bias typically linked to prior probabilities (Layher et al., 2020).

The drift diffusion model (DDM) builds upon SDT but surpasses it in certain respects. A significant advantage of DDM is its consideration of both response time and accuracy, which helps resolve issues arising from employing different measures for inhibition and updating tasks (Chwiesko et al., 2023). DDM provides a more nuanced breakdown of cognitive processes by dividing total decision time into non-decision time and decision time (Myers et al., 2022; Ratcliff, 1978; Ratcliff & McKoon, 2008), facilitating a more granular understanding of how inhibition

impacts the cognitive processes underlying updating. Additionally, DDM addresses data discrepancies caused by various raw reaction time processing methods and aids in extracting parameters related to the speed-accuracy trade-off in experiments (Draheim et al., 2019; Rey-Mermet et al., 2019). According to DDM, decision-making is viewed as an evidence accumulation process, where a judgment is made once the evidence for one option meets a decision threshold (Forstmann et al., 2016). DDM breaks down reaction times on a trial-by-trial basis into underlying decision processes, represented by several psychological parameters (**Figure 2**): (1) decision threshold (*a*), which indicates the information quantity needed to make a decision and symbolizes the participants' speed/accuracy trade-off or cautiousness. A higher threshold suggests slower yet more precise responses; (2) drift rate (*v*), which signifies the rate and potency of evidence accumulation over time; (3) non-decision time (*t*), which represents the duration of processes that are not related to decision-making (e.g., perceptual encoding of stimuli and motor responses) (Ratcliff, 1978; Ratcliff et al., 2016). A longer non-decision time can suggest the recruitment of additional attentional resources (Servant & Evans, 2020); (4) starting point (*z*), reflecting a predisposition toward one response before evidence accumulation starts (Voss et al., 2004; White & Poldrack, 2014). The hierarchical version of DDM, HDDM, has demonstrated effectiveness in estimating model parameters with fewer trials (Lerche et al., 2017; Wiecki et al., 2013).

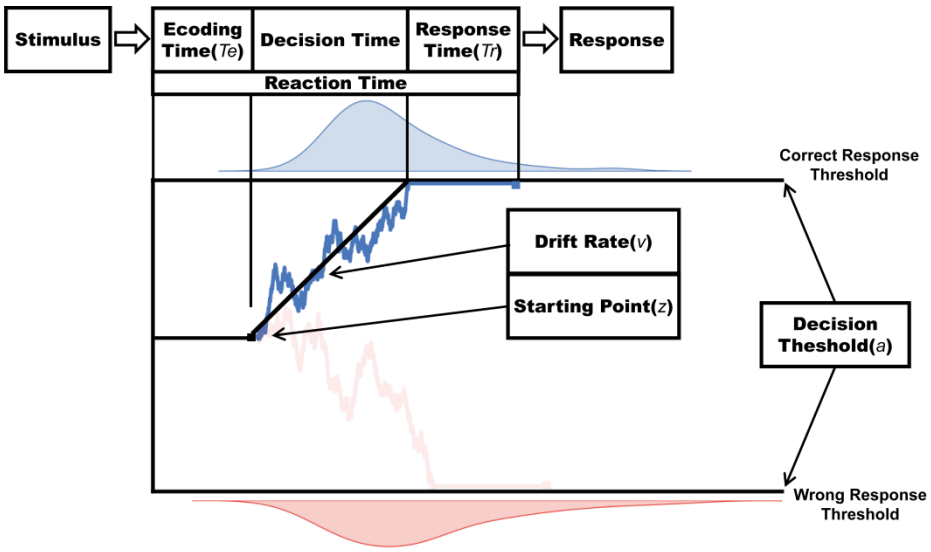


Figure 2. Drift Diffusion Model (DDM) Schematic.

Among the parameters in the DDM, drift rate (*v*) is a critical indicator. Prior research on the psychometric characteristics of the drift rate parameter shows that it reflects both the general cognitive ability (i.e., the speed of

information accumulation necessary for completing all tasks) and cognitive processes specific to certain task conditions (Lerche et al., 2020; Schubert et al., 2016). Moreover, drift rate has exhibited good retest reliability (Lerche & Voss, 2017; Schubert et al., 2016). Based on drift rate, researchers have discovered evidence supporting the hypothesis that inhibition and updating share cognitive resources. Löffler et al. (2024) found that by evaluating drift rate across various inhibition and updating tasks, inhibition and updating were associated with a common executive function factor, implying that the two processes might share cognitive mechanisms. Thus, we hypothesize that inhibition and updating share cognitive resources. According to the dual-task paradigm (Lavie, 2005, 2010; Lavie et al., 2004; Wei et al., 2022; Wei & Zhou, 2020), if inhibition and updating do indeed share cognitive resources, performance impairments would be evident in tasks requiring both processes, leading to a lower drift rate, even when considering the CSE effect.

In conclusion, this study investigates whether inhibition and updating share cognitive resources. We propose that inhibition and updating share cognitive resources, such that when inhibition is required, updating performance is impaired even when controlling the CSE and the color-word congruency of current stimulus.

2. Experiment

2.1 Materials and Method

2.1.1 Participants

A total of 74 participants were initially recruited, but four left-handed participants were excluded from the analysis. As a result, the final sample consisted of 70 right-handed participants (39 males, 31 females), with ages ranging from 18 to 25 years (M = 19.90, SD = 1.35). All participants signed informed consent forms before the experiment. The experimental procedures were conducted in accordance with the ethical standards of the local ethics committee. Participants were rewarded with at least 15 CNY after completing the experiment.

2.1.2 Materials

Stimulus materials comprised four Chinese color words (“red”, “yellow”, “blue”, and “green” in Chinese) displayed in 80-point SimSun font, with each word presented in all four colors. The RGB values were: red (255, 0, 0), green (0, 255, 0), yellow (255, 255, 0), and blue (0, 176, 240). Each image (1280 × 720 pixels) combined one of the four words with one of the four colors, yielding 16 unique stimuli. All images had a resolution of 1,280 × 720

pixels, resulting in a total of 16 (4 × 4) stimulus images. Based on the stimulus-task compatibility types of adjacent trials, eight categories were established: II (both trials involve incompatible stimulus-task), IC (previous trials involve incompatible stimulus-task, current trial involve compatible stimulus-task), CC (both trials involve incompatible stimulus-task), and CI (previous trial involves incompatible stimulus-task, current trial involves compatible stimulus-task). Additionally, the color-word congruency of the current stimulus (incongruent/congruent) was considered, resulting in 8 conditions (2 × 2 × 2 combinations). Inhibition was required for trials where there was an incompatible stimulus-task relationship (**Figure 1.C**). The experiment consisted of 198 trials, including two non-response trials at the beginning of each block. Half of the trials (98) required inhibition and updating, while the other half only required only updating. The distribution of trial types was as follows: 48 each for II, IC, and CC, and 47 for CI. Stimuli were presented in a pseudo-random order to prevent repetition priming effects (Egner, 2007), ensuring no consecutive identical stimuli were presented. Moreover, the correct response keys ("F" and "J") were balanced across trials (Egner & Hirsch, 2005).

2.1.3 Experimental Design

The experiment employed a within-subjects design with a 2 (Previous Stimulus-Task Compatibility: Incompatible vs. Compatible) × 2 (Current Stimulus-Task Compatibility: Incompatible vs. Compatible) × 2 (Color-Word Congruency of the Current Stimulus: Incongruent vs. Congruent) factorial structure. The dependent variables were reaction time and accuracy.

2.1.4 Experimental Procedure

Stimuli were presented using E-Prime 2.0 (Psychology Software Tools). Each trial began with a fixation cross ("+") displayed at the center of the screen for 1,500 ms, followed by a Chinese character. Participants were instructed to quickly and accurately judge whether the color-word congruency of the current character matched the color-word congruency of the previous trial. They were instructed to press "J" with their left index finger for "same" and "F" with their right index finger for "different". Stimulus presentation lasted for 2,000 ms or until a response was recorded. To minimize the anticipation effect and reduce moderate variability that could influence response control (Wodka et al., 2009), a blank screen was presented for a jittered duration of 900~1,200 ms (jittered in 100-ms increments). The first trial of each block did not require a response (**Figure 3**).

Prior to the formal experiment, participants completed a practice block of 20 valid trials to familiarize themselves with the experimental procedure and key responses. Feedback on accuracy was provided at the end of

the practice phase, and participants were reminded to ensure they fully understood the task before proceeding to the formal experiment. After completing 98 trials, participants were given a rest period, the duration of which was self-determined. The entire session lasted approximately 20 minutes.

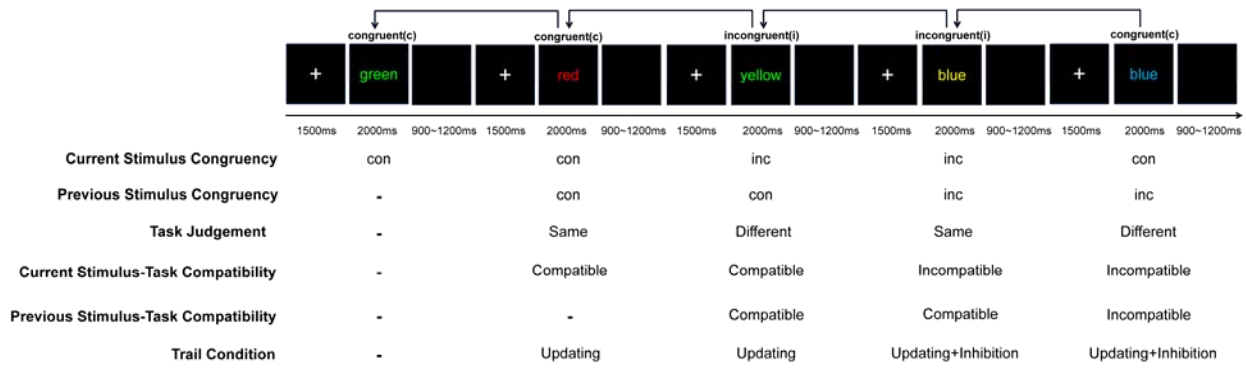


Figure 3. Experimental Procedure.

2.1.5 Behavioral Data Analysis

In analyzing reaction times, we excluded data from error trials and post-error trials (29.92%), as well as trials with reaction times below 200ms (0.7%), to minimize the influence of erroneous responses on subsequent trials. To examine the CSE in our task, we calculated CSE using the following formula: CSE = (CI - CC) - (II - IC).

We applied Bayesian statistics in all our analyses. Unlike *p*-values, which only indicate the likelihood of the null hypothesis being true, Bayes Factors offer a continuous measure of evidence that supports more informed decisions about hypothesis testing (Halsey, 2019; Wagenmakers et al., 2018). To examine the effects of current and previous trial types on performance, we conducted a within-subjects 2 (Previous Stimulus-Task Compatibility: Incompatible vs. Compatible) × 2 (Current Stimulus-Task Compatibility: Incompatible vs. Compatible) × 2 (Color-Word Congruency of the Current Stimulus: Incongruent vs. Congruent) Bayesian ANOVA using JASP software (V0.19.3; JASP Team, 2024) for both mean RTs and ACCs. Since no a priori information was available about the effects, we used default prior settings (r = .5 for fixed effects, r = 1 for random effects) as recommended in previous literature (Rouder et al., 2012). Bayesian analysis provides an alternative to traditional null hypothesis significance testing by offering Bayes factors. This factor quantifies the evidence for the alternative hypothesis (H_1) over the null hypothesis (H_0). In our study, Bayes factors were used to compare two competing models in t-tests and post-hoc tests (BF_{10}), while inclusion Bayes factors (BF_{incl}) evaluated the inclusion of predictors in ANOVA. Besides, we reported the standardized effect size δ in t-test (i.e., the population version of Cohen's *d*, the standardized difference

in mean fuse times). For parameter estimation, δ was assigned a Cauchy prior distribution with $r = 1/\sqrt{2}$ (Van Doorn et al., 2021). Based on previous research on interpreting Bayes factors (Jarosz & Wiley, 2014; Jeffreys, 1998; Wetzels et al., 2011), BF_{10} values greater than 1 indicate stronger support for H_1, whereas values less than 1 indicate stronger support for H_0. We adopted the classification scheme for BF values outlined by Lee and Wagenmakers (Lee & Wagenmakers, 2014; Speiger et al., 2025): Evidence for the H_1 is considered anecdotal for a BF_{10} between 1 and 3, moderate for a BF_{10} between 3 and 10, strong for a BF_{10} greater than 10, very strong for a BF_{10} greater than 30, and extreme for a BF_{10} greater than 100. Conversely, evidence for the H_0 is considered anecdotal for a BF_{10} between 1 and 1/3, moderate for a BF_{10} between 1/3 and 1/10, strong for a BF_{10} smaller than 1/10, very strong for a BF_{10} smaller than 1/30, and extreme for a BF_{10} smaller than 1/100.

2.1.6 SDT Analysis

Signal detection analysis was conducted, and extreme values were adjusted using the R package *psych* (Makowski, 2018). In this analysis, hits were defined as correct responses when the color-word congruency of the current and previous stimuli was the same, while misses were defined as incorrect responses under the same condition. False Alarms (FA) were defined as incorrect responses when the color-word congruency of the current stimulus differed from the previous one, and Correct Rejections (CR) were correct responses in this situation (**Figure 4**). The sensitivity index *d*' measured updating performance, calculated as z(H) - z(F), where H and F represent the hit rate and false alarm rate, respectively. Response bias *c*, defined as the tendency to judge the current stimulus as target or non-target, was calculated as -0.5[z(H) + z(F)]. Based on our hypotheses, the signal detection analysis primarily focused on examining the interaction between current stimulus-task compatibility and previous stimulus-task compatibility to investigate the influence of inhibition on updating, while also considering the potential effect of the CSE.

Previous con (Current Compatibility)	Judgement "Same"	Judgement "Different"
Current Stimulate: inc	False alarm (ci)	Correct reject (ci)
Current Stimulate: con	Hit (cc)	Miss (cc)

Previous inc (Current Incompatibility)	Judgement "Same"	Judgement "Different"
Current Stimulate: inc	Hit (ii)	Miss (ii)
Current Stimulate: con	False alarm (ic)	Correct reject (ic)

Figure 4. Signal Detection Theory Classification Diagram. In this diagram, green represents correct responses, and red represents incorrect responses.

2.1.7 HDDM Analysis

Data modeling was conducted using the Python package HDDM (V0.9.8) within the docker framework (Pan et al., 2025; Wiecki et al., 2013). Based on our experimental objectives and paradigm, we hypothesized that current stimulus-task compatibility would affect the drift rate, decision threshold, and non-decision time of updating. Given that color-word congruency (congruent/incongruent) is central to our task, we anticipated that color-word incongruent trials might demand more cognitive resources during the decision-making process, as participants encounter semantic conflict in these trials. Furthermore, visual properties of the current stimulus (e.g., color and brightness) were expected to influence perceptual processes during the non-decision stage (Bompas et al., 2024). Thus, we assumed that the attribute of the current stimulus would affect both drift rate and non-decision time. Regarding the potential influence of the CSE, computational modeling studies have suggested that following inhibitory trials, the activation of task-irrelevant information decreases (Koob et al., 2023; Luo & Proctor, 2022). Based on this, we predicted that the compatibility of the previous stimulus-task would impact both the drift rate and non-decision time. Since the same/different responses were balanced across trials, we set a neutral starting point (z) for all models. We tested four models, as outlined in Table 1.

Model 1 served as the baseline model, including only the effect of inhibition (current stimulus-task compatibility) and current stimulus attributes (color-word congruency of the current stimulus). Models 2, 3, and 4 were more comprehensive, incorporating the CSE (previous stimulus-task compatibility). In Model 1, we allowed drift rate (v), and non-decision time (t) to vary according to current stimulus-task compatibility and color-word congruency of the current stimulus, and decision threshold (a) to vary with current stimulus-task compatibility. This model aimed to explore whether inhibition and stimulus attributes influence the updating process. Model 2 extended this by allowing drift rate (v) to vary according to previous stimulus-task compatibility, examining the potential impact of the CSE on the decision process. Model 3, based on Model 1, allowed non-decision time (t) to vary with the previous stimulus-task compatibility, investigating whether the previous stimulus-task compatibility influences the non-decision phase. Model 4 expanded upon Model 1 by considering previous stimulus-task compatibility as a factor influencing both drift rate (v), and non-decision time (t).

To ensure model convergence and data validity, trials with no response or reaction times below 200ms were excluded (4.14%). For all models, parameters were estimated by drawing 10,000 samples and discarding the first 2,000. Model convergence was assessed through visual inspection of chains and calculation of the Gelman-Rubin

statistic, with $\hat{R} < 1.01$ indicating good convergence (Gelman et al., 2013). We also used the Deviance Information Criterion (DIC) as an approximation of Bayesian model evidence for model comparison, where lower DIC values are favorable, indicating a better model fit to the data (Frank et al., 2015; Spiegelhalter et al., 2002). All four models converged and were validated through posterior predictive checks of reaction time and accuracy (For model 4 posterior predictive checks, see **Appendix Figure 1**).

Table 1 Summary of Hierarchical Drift Diffusion Models

Model	Model structure	DIC
Model 1	Previous stimulus-task compatibility{none}, Current stimulus-task compatibility{□ (C), □ (C), *t* (C)}, Current stimulus congruency{□ (c), *t* (c)}	15606.36
Model 2	Previous stimulus-task compatibility{□ (P)}, Current stimulus-task compatibility{□ (C), □ (C), *t* (C)}, Current stimulus congruency{□ (c), *t* (c)}	13954.15
Model 3	Previous stimulus-task compatibility{*t* (P)}, Current stimulus-task compatibility{□ (C), □ (C), *t* (C)}, Current stimulus congruency{□ (c), *t* (c)}	13811.46
Model 4	Previous stimulus-task compatibility{□ (P), *t* (P)}, Current stimulus-task compatibility{□ (C), □ (C), *t* (C)}, Current stimulus congruency{□ (c), *t* (c)}	13016.95

***Note*:** Models of different complexity (number of hierarchical levels (P: Previous stimulus-task compatibility, C: Current stimulus-task compatibility, c: Current stimulus congruency) and permitted variation of model parameters (*a*: Decision Threshold, *t*: Non-decision Time, □: Drift Rate) across these levels) that were fitted to the data and their Deviance Information Criterions (DICs). Based on the lowest DIC, Model 4 was chosen for analysis.

2.2 Results

2.2.1 Behavioral Results

Regarding reaction times (**Figure 4.A, Appendix Table 1**), the Bayesian ANOVA provided extremely strong evidence for a main effect of current stimulus-task compatibility ($BF_{incl} = 1.58 \times 10^8$). Specifically, extremely strong evidence supported the reaction times for current incompatible trials (*M* = 1129.63, *SE* = 17.38) were longer than compatible trials (*M* = 1025.88, *SE* = 15.49, $BF_{10} = 1.22 \times 10^4$). Additionally, extremely strong evidence was found for the main effect of previous stimulus-task compatibility ($BF_{incl} = 1120.28$), where anecdotal evidence supported reaction times for previous incompatible trials (*M* = 1102.88, *SE* = 17.16) were longer than those compatible trials (*M* = 1048.92, *SE* = 14.11, $BF_{10} = 1.60$). Furthermore, there was extremely strong evidence for a

main effect of color-word congruency of the current stimulus ($BF_{incl} = 5.64 \times 10^6$), with extremely strong evidence supported the reaction times for incongruent current stimuli (*M* = 1095.72, *SE* = 15.79) longer than congruent ones (*M* = 1052.48, *SE* = 15.36, $BF_{10} = 1.04 \times 10^5$), suggesting that the incongruent color-word attribute of the current stimulus leads to longer reaction times. For interaction, there was extremely strong evidence supporting two-way interaction. One between current stimulus-task compatibility and previous stimulus-task compatibility, and another between current stimulus-task compatibility and color-word congruency of the current stimulus (Both $BF_{incl} \geq 1.40 \times 10^{15}$). In contrast, anecdotal evidence was against an interaction between previous stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 0.59$). Most importantly, there was extremely strong evidence supporting a three-way interaction among previous stimulus-task compatibility, current stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 343.68$). Post-hoc analysis revealed that the interactions between previous and current stimulus-task compatibility varied between the color-word congruency of current stimulus. In both the incongruent and congruent current stimuli, the result showed the CSE (RT CSE > 0). Pairwise post-hoc tests revealed very strong evidence that CSE was larger when the current color-word was incongruent (*M* = 503.45, *SE* = 26.27) compared to congruent (*M* = 403.45, *SE* = 27.70, $BF_{10} = 93.40$, δ posterior median = 0.45, 95% CI [0.20, 0.69]). Finally, to minimize the potential influence of the CSE and current stimulus attributes on the results, we analyzed only the condition where the previous trial's stimulus-task compatibility was compatible and the color-word congruency of current stimulus was congruent, there was extremely strong evidence that reaction times were longer for current incompatible trials (*M* = 1255.22, *SE* = 21.04) than for current compatible trials (*M* = 847.80, *SE* = 17.61, $BF_{10} = 3.12 \times 10^{29}$). This result indicated that, after controlling for potential confounding factors, conditions requiring both inhibition and updating led to longer reaction times compared to those requiring only updating.

Regarding accuracy (**Figure 4.B, Appendix Table 1**), the Bayesian ANOVA provided extremely strong evidence for a main effect of current stimulus-task compatibility ($BF_{incl} = 1759.87$), with very strong evidence supported the accuracy for incompatible trials (*M* = 0.81, *SE* = 0.01) was lower compared to compatible trials (*M* = 0.85, *SE* = 0.08, $BF_{10} = 36.17$). In contrast, there was moderate evidence against a main effect of previous stimulus-task compatibility ($BF_{incl} = 0.11$) and anecdotal evidence against a main effect of color-word congruency of the current stimulus ($BF_{incl} = 0.52$). Moreover, there was extremely strong evidence supporting a two-way

interaction between previous and current stimulus-task compatibility ($BF_{incl} = 8.86 \times 10^{25}$). Most importantly, there was very strong evidence supporting a three-way interaction among previous stimulus-task compatibility, current stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 61.21$). Post-hoc analysis revealed that the interactions between previous and current stimulus-task compatibility varied between the color-word congruency of current stimulus. In both the incongruent and congruent current stimuli, the result showed the CSE (ACC CSE < 0). Pairwise post-hoc tests revealed strong evidence that CSE was larger when the color-word congruency of current stimulus was incongruent (*M* = -0.36, *SE* = 0.02) compared to congruent (*M* = -0.28, *SE* = 0.02, $BF_{10} = 10.49$, δ posterior median = -0.36, 95% CI [-0.60, -0.12]). Finally, to minimize the potential influence of the CSE and current stimulus attributes on the results, we analyzed only the condition where the previous trial's stimulus-task compatibility was compatible and color-word congruency of the current stimulus was congruent, there was extremely strong evidence that accuracy for current incompatible trials (*M* = 0.74, *SE* = 0.02) was lower than for current compatible trials (*M* = 0.93, *SE* = 0.01, $BF_{10} = 4.75 \times 10^{13}$). This result indicated that, after controlling for potential confounding factors, conditions requiring both inhibition and updating led to lower accuracy compared to those requiring only updating.

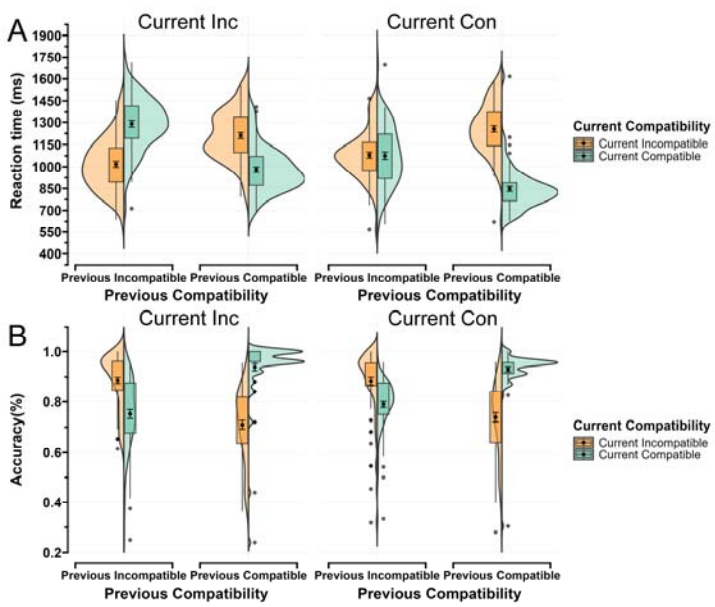


Figure 4. Behavioral Results. (A) Split-violin plot of reaction time. (B) Split-violin plot of accuracy. ***Note*:** In each split-violin plot, the midpoint of the box plot represents the mean of the data. The error bars around the midpoint

represent the Standard Error of the Mean (SEM). The upper and lower limits of the box represent the third quartile (Q3, 75th percentile) and first quartile (Q1, 25th percentile) of the data, respectively. The whiskers extend to 1.5 times the interquartile range; data points beyond this are considered outliers. The width of the split-violin plot reflects the density of data points at different values.

2.2.2 SDT Results

Regarding *d'* (**Figure 5.A, Appendix Table 2**), Bayesian ANOVA revealed strong evidence for a main effect of current stimulus-task compatibility in *d'* ($BF_{incl} = 1724.87$), with moderate evidence supported the *d'* for current incompatible trials was lower compared to compatible trials ($BF_{10} = 3.26$). In contrast, there was strong evidence against a main effect of previous stimulus-task compatibility ($BF_{incl} = 0.22$). Additionally, extremely strong evidence supported a two-way interaction between previous and current stimulus-task compatibility ($BF_{incl} = 4.57 \times 10^{61}$). For incompatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the *d'* of current incompatible trials (*M* = 2.53, *SE* = 0.12) was higher compared to current compatible trials (II vs. IC: *M* = 1.50, *SE* = 0.07, $BF_{10} = 8.62 \times 10^{11}$, δ posterior median=1.15, 95% CI [0.85, 1.46]). For compatible previous trials, there was extremely strong evidence that *d'* for current incompatible trials (*M* = 1.24, *SE* = 0.09) was lower than for current compatible trials (CI vs. CC: *M* = 3.02, *SE* = 0.09, $BF_{10} = 1.40 \times 10^{26}$, δ posterior median =-1.27, 95% CI [-1.59, -0.95]). This result indicated that, after controlling for potential confounding from CSE, conditions requiring both inhibition and updating led to lower *d'* compared to those requiring only updating.

Regarding decision bias (*c*) (**Appendix Table 2**), Bayesian ANOVA revealed strong evidence against a main effect of current stimulus-task compatibility *c* ($BF_{incl} = 0.16$), but showed very strong evidence supporting a main effect of previous stimulus-task compatibility ($BF_{incl} = 31.55$), with very strong evidence indicating that *c* for previously incompatible trials was lower than for compatible trials ($BF_{10} = 51.73$). This suggested that experiencing conflict reduces subsequent caution in updating. Besides, there was moderate evidence against the interaction between previous and current stimulus-task compatibility ($BF_{incl} = 0.55$).

Regarding hit rate (**Figure 5.B, Appendix Table 2**), Bayesian ANOVA revealed very strong evidence supported a main effect of current stimulus-task compatibility ($BF_{incl} = 71.17$), with strong evidence supporting the hit rate for incompatible trials was lower compared to compatible trials ($BF_{10} = 25.53$). However, there was strong

evidence against a main effect of current stimulus-task compatibility ($BF_{incl} = 0.25$). Furthermore, extremely strong evidence supported a two-way interaction between previous and current stimulus-task compatibility ($BF_{incl} = 5.53 \times 10^{39}$). For incompatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the hit rate of current incompatible trials was higher compared to current compatible trials (II vs. IC: $BF_{10} = 3.04 \times 10^{7}$, δ posterior median=0.85, 95% CI [0.58, 1.13]). For compatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the hit rate of current incompatible trials was lower compared to current incompatible trials (CI vs. CC: $BF_{10} = 4.53 \times 10^{13}$, δ posterior median=-1.27, 95% CI [-1.59, -0.95]). This result indicated that, after controlling for potential confounding from CSE, conditions requiring both inhibition and updating led to lower hit rate compared to those requiring only updating.

Regarding correct rejection (**Figure 5.C, Appendix Table 2**), Bayesian ANOVA revealed anecdotal evidence against a main effect of current stimulus-task compatibility ($BF_{incl} = 0.88$), and strong evidence against a main effect of previous stimulus-task compatibility ($BF_{incl} = 0.29$). There was extremely strong evidence supporting a two-way interaction between previous and current stimulus-task compatibility ($BF_{incl} = 8.70 \times 10^{33}$). For incompatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the correct rejection rate of current incompatible trials (*M* = 0.88, *SE* = 0.02) was higher compared to current incompatible trials (II vs. IC: *M* = 0.75, *SE* = 0.02, $BF_{10} = 4.35 \times 10^{7}$, δ posterior median=0.86, 95% CI [0.59, 1.14]). For compatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the correct rejection rate of current incompatible trials (*M* = 0.74, *SE* = 0.02) was lower compared to current incompatible trials (CI vs. CC: *M* = 0.94, *SE* = 0.01, $BF_{10} = 2.15 \times 10^{16}$, δ posterior median=-1.46, 95% CI [-1.81, -1.12]). This result indicated that, after controlling for potential confounding from CSE, conditions requiring both inhibition and updating led to lower correct rejection rate compared to those requiring only updating.

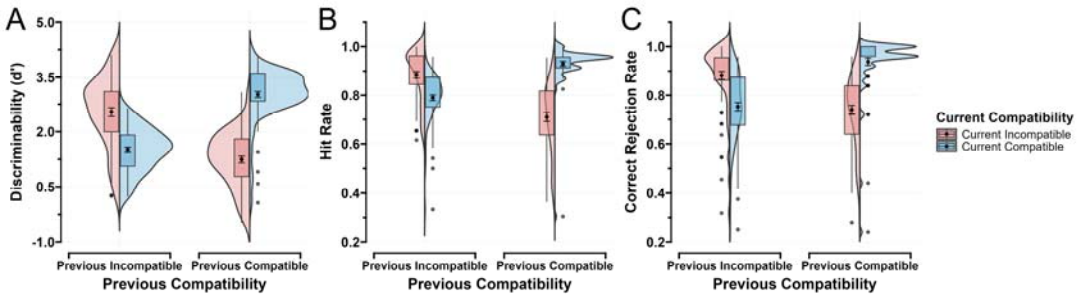


Figure 5. Signal Detection Analysis Results. (A) Split-violin plot of discriminability (*d*'). (B) Split-violin plot of hit rate. (C) Split-violin plot of correct rejection. ***Note*:** In each split-violin plot, the midpoint of the box plot represents the mean of the data. The error bars around the midpoint represent the Standard Error of the Mean (SEM). The upper and lower limits of the box represent the third quartile (Q3, 75th percentile) and first quartile (Q1, 25th percentile) of the data, respectively. The whiskers extend to 1.5 times the interquartile range; data points beyond this are considered outliers. The width of the split-violin plot reflects the density of data points at different values.

2.2.3 HDDM Results

Based on the DIC and model comparison, HDDM revealed that Model 4 provided the best fit (**Figure 6**). This suggests that the previous stimulus-task compatibility affects both drift rate (*v*) and non-decision time (*t*). Therefore, we selected Model 4 as the best-fitting model and proceeded with parameter analysis.

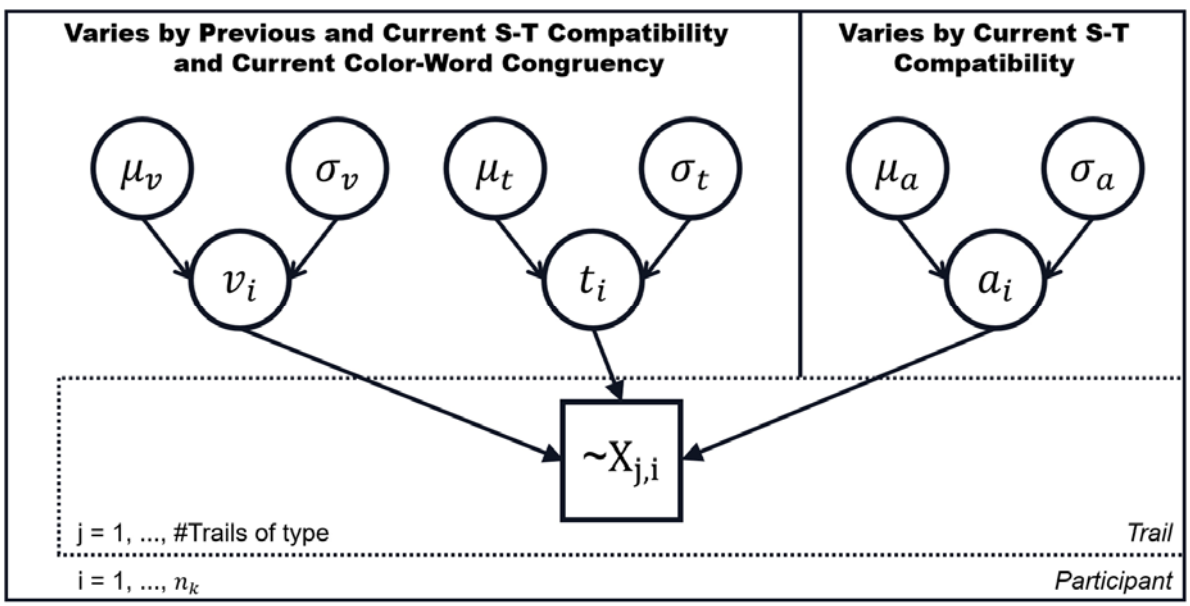


Figure 6. Best-fitting Hierarchical Bayesian Model Used for Estimating HDDM Parameters. The inner plate represents the participant level, while the outer plate corresponds to the group-level parameters. *v* = drift rate, *t* = non-decision time, *a* = decision threshold. Each trial is denoted as $X_{j,i}$. The best-fitting hierarchical model allowed drift rate, decision threshold, and non-decision time to vary by trial type. Specifically, drift rate (*v*) and non-decision time (*t*) varied based on previous and current stimulus-task compatibility and color-word congruency of the current stimulus. Meanwhile, decision threshold (*a*) was only modulated by current stimulus-task compatibility.

Drift rate (*v*) and non-decision time (*t*) were analyzed using Bayesian repeated measures ANOVA, while the decision threshold (*a*) was analyzed using Bayesian paired samples t-test (**Figure 7, detail statistics see Appendix Table 3**).

For drift rate (*v*), the analysis provided extremely strong evidence for the main effect of current ($BF_{incl} = 2.43 \times 10^{16}$), previous ($BF_{incl} = 6.05 \times 10^{9}$) stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 1.81 \times 10^{5}$). Specifically, extremely strong evidence supported the drift rates (*v*) of current incompatible trials being lower compared to compatible trials ($BF_{10} = 4.16 \times 10^{5}$), strong evidence supported previous incompatible trials being lower than previous compatible trials ($BF_{10} = 9.82$), and extremely strong evidence supported current incongruent stimuli being lower than congruent stimuli ($BF_{10} = 7.42 \times 10^{5}$). Furthermore, extremely strong evidence supported a two-way interaction between previous and current stimulus-task compatibility ($BF_{incl} = 1.90 \times 10^{42}$). For incompatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the drift rate (*v*) of current incompatible trials was higher compared to current compatible trials (II vs. IC: $BF_{10} = 5.33 \times 10^{18}$, δ posterior median=1.64, 95% CI [1.28, 2.01]). For compatible previous trials, pairwise post-hoc tests revealed extremely strong evidence that the hit rate of current incompatible trials were lower compared to current incompatible trials (CI vs. CC: $BF_{10} = 5.08 \times 10^{41}$). This result indicated that, after controlling for potential confounding from CSE, conditions requiring both inhibition and updating led to lower drift rate compared to those requiring only updating. Besides, there was moderate evidence supporting an interaction between current stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 1.93$). In contrast, there was moderate evidence against an interaction between previous stimulus-task compatibility and current stimulus congruency ($BF_{incl} = 0.17$). Moreover, there was anecdotal evidence against a three-way interaction between previous stimulus-task compatibility, current stimulus-task compatibility and current stimulus congruency ($BF_{incl} = 0.45$).

For non-decision time (*t*), the analysis yielded extremely strong evidence for a main effect of current stimulus-task compatibility ($BF_{incl} = 9.53 \times 10^{10}$), strong evidence for a main effect of previous stimulus-task compatibility ($BF_{incl} = 3.85$), and extremely strong evidence for a main effect of color-word congruency of the current stimulus ($BF_{incl} = 737.06$). Specifically, extremely strong evidence supported the non-decision time (*t*) of current incompatible trials being shorter compared to compatible trials ($BF_{10} = 8.50 \times 10^{9}$), anecdotal evidence

supported previous incompatible trials being longer than previous compatible trials ($BF_{10} = 1.80$), and extremely strong evidence supported current incongruent stimuli being longer than congruent stimuli ($BF_{10} = 754.51$). Additionally, anecdotal evidence supported an interaction between previous stimulus-task compatibility and current stimulus congruency ($BF_{incl} = 2.01$). There was extremely strong evidence for two way interaction between previous and current stimulus-task compatibility ($BF_{incl} = 2.96 \times 10^{10}$), current stimulus-task compatibility and current stimulus congruency ($BF_{incl} = 8.15 \times 10^{6}$). Most importantly, there was extremely strong evidence supporting a three-way interaction among previous stimulus-task compatibility, current stimulus-task compatibility and color-word congruency of the current stimulus ($BF_{incl} = 2.59 \times 10^{6}$). Post-hoc analysis revealed that the interactions between previous and current stimulus-task compatibility varied between current stimulus congruency. In both the incongruent and congruent current stimulus, the result showed the CSE (*t* CSE > 0). Pairwise post-hoc tests revealed strong evidence that CSE was larger when the current stimulus was incongruent (*M* = 0.20, *SE* = 0.02) compared to congruent (*M* = 0.12, *SE* = 0.02, $BF_{10} = 47.05$, δ posterior median=0.42, 95% CI [0.18, 0.66]). Finally, to minimize the potential influence of the CSE and current stimulus attributes on the results, we analyzed only the condition where the previous trial's stimulus-task compatibility was compatible and the current stimulus was congruent. There was extremely strong evidence that non-decision time (*t*) for current incompatible trials (*M* = 0.75, *SE* = 0.02) was longer than for current compatible trials (*M* = 0.48, *SE* = 0.01, $BF_{10} = 2.41 \times 10^{29}$). This result indicated that, after controlling for potential confounding factors, conditions requiring both inhibition and updating led to longer non-decision time compared to those requiring only updating.

For decision threshold (*a*), the result revealed extremely strong evidence that the decision threshold (*a*) of current incompatible stimulus-task trials (*M* = 1.66, *SE* = 0.01) was lower than current compatible trials (*M* = 1.72, *SE* = 0.01, $BF_{10} = 8872.37$, δ posterior median=-0.60, 95% CI [-0.86, -0.35]) .

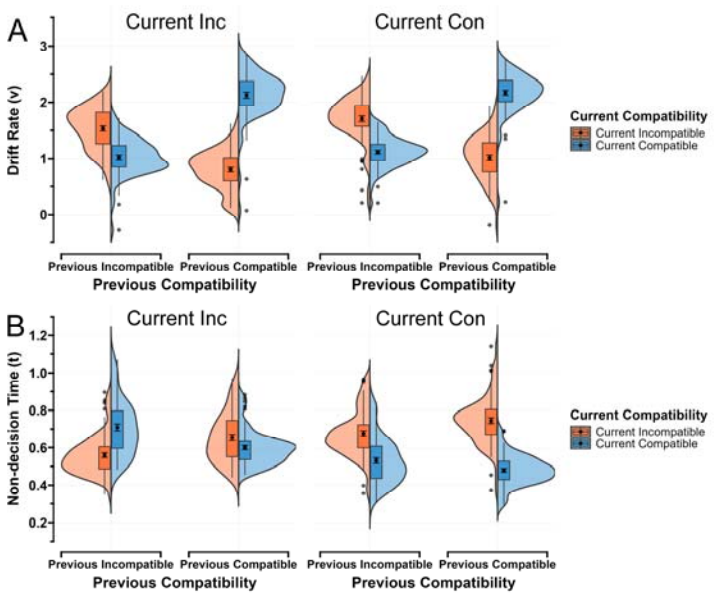


Figure 7. Group-level Results of Drift Diffusion Model Parameters. (A) Split-violin plot of drift rate. (B) Split-violin plot of non-decision time. ***Note*:** In each split-violin plot, the midpoint of the box plot represents the mean of the data. The error bars around the midpoint represent the Standard Error of the Mean (SEM). The upper and lower limits of the box represent the third quartile (Q3, 75th percentile) and first quartile (Q1, 25th percentile) of the data, respectively. The whiskers extend to 1.5 times the interquartile range; data points beyond this are considered outliers. The width of the split-violin plot reflects the density of data points at different values.

2.2.4 Exploratory Analysis: Magnitude of the stimulus-task incompatibility effects

To demonstrating the effectiveness of our manipulation of the expected inhibition constructs, we analyzed the effect sizes of the current stimulus-task incompatibility measurements and compared them with the effect sizes (Cohen's *d*) from previous Stroop task (Table 2).

When the effects of the CSE and color-word congruency of the current stimulus were not controlled (comparing current incompatible vs. current compatible trials), the inhibition's effect size for reaction time was Cohen's $d = 0.99$, and the effect size for accuracy was Cohen's $d = 0.56$. After controlling for the CSE and current stimulus congruency effects (comparing CIc vs. CCc), the inhibition's effect size for reaction time increased to Cohen's $d = 2.62$, and the effect size for accuracy increased to Cohen's $d = 1.30$. Except for the accuracy effect size when CSE and current stimulus congruency effects were not excluded (which was moderate, greater than 0.5 but

less than 0.8), the effect sizes in all other cases were greater than 0.8, which is commonly considered as the threshold for large effect sizes.

We selected the Stroop task dataset[1] from a recently published study with very strict participant selection criteria to demonstrate the traditional tasks' effect size of inhibition (Bissett et al., 2024). For the traditional Stroop effect (comparing Stroop incongruent vs. congruent trials), the inhibition's effect size for reaction time was Cohen's d = 1.57, and the effect size for accuracy was Cohen's d = 0.57. After controlling for the CSE (comparing ci vs. cc), the inhibition's effect size for reaction time decreased to Cohen's d = 1.25, and the effect size for accuracy decreased to Cohen's d = 0.49. Comparing our task's effect sizes to the traditional Stroop effect, we found that after excluding the CSE and current stimulus congruency effects, our task exhibited a larger effect size. This suggested that our task may have greater sensitivity in measuring inhibition, reflecting the effectiveness of our task in assessing inhibitory control structures. Even without excluding the CSE and current stimulus congruency effects, our task showed a comparable effect size in accuracy (Cohen's d = 0.56) to the traditional task (Cohen's d = 0.57), while the effect size for reaction time exceeded 0.8, indicating a large effect. Overall, our task effectively measures inhibitory control and reflects the shared relationship between inhibition and updating.

Table 2 Summary of Inhibition Effect Size Presented As Mean (*SE*)

Task		Reaction Time	Accuracy
Our Task	**Original**	103.76 (12.47)	-0.05 (0.01)
	Control	407.42 (18.60)	-0.19 (0.02)
Stroop	**Original**	97.35 (6.01)	-0.03 (0.01)
	Control	104.10 (8.14)	-0.04 (0.01)

3. Discussion

Past research on inhibition and updating has typically examined these functions separately using distinct paradigms and different performance indicators. Such approaches often neglect the speed-accuracy trade-off, making it difficult to determine whether the relationship between inhibition and updating is shared or distinct. To

[1] To ensure consistency in data exclusion criteria, we applied the same standards as in the current experiment. For reaction time analyses, we excluded error trials and post-error trials (9.17%), as well as trials with reaction times below 200 ms or above 2,000 ms (0.05%). Additionally, one participant with an accuracy below 50% was excluded, resulting in a final dataset of 104 participants. The compared dataset is available at our OSF link.

address these limitations, this study investigated the relationship between inhibition and updating within a unified task framework using an innovative paradigm. By integrating signal detection theory and HDDM, we found that, regardless of the influence of the CSE, concurrent processing of inhibition impaired updating performance, suggesting that these two functions rely on shared cognitive resources. Furthermore, when comparing the inhibition effect size in our novel task with that of the traditional Stroop task, our task demonstrated a satisfactory Cohen's *d*, further supporting its effectiveness in measuring inhibition within an updating context.

The findings support our hypothesis that inhibition and updating share cognitive resources, as evidenced by both behavioral and model-based results. Behaviorally, current incompatible stimulus-task trials resulted in increased reaction times and error rates, indicating resource competition between inhibition and updating. Signal detection analysis further provided extremely strong evidence for a decline in participants' discriminability (*d'*) when inhibition was necessary, suggesting that cognitive resources typically allocated to updating were depleted, impairing stimulus differentiation. Computational modeling (HDDM) results further supported this view. The drift rate decreased when inhibition was needed, indicating slower evidence accumulation in the updating progress. Additionally, a lower decision threshold was observed in current incompatible stimulus-task trials, suggesting that concurrent inhibition reduced the amount of evidence accumulation needed for updating for updating, further supporting the idea that these processes share common resources. Moreover, extremely strong evidence showed longer non-decision times in current incompatible stimulus-task trials, suggesting that inhibition influenced the response execution stage, consuming additional cognitive resources (Bompas et al., 2024; Servant & Evans, 2020). However, potential confounds such as the CSE may have influenced our findings. To assess whether CSE was present, we analyzed the interaction between previous and current stimulus-task compatibility. For measures that exhibited only a two-way interaction between previous and current stimulus-task compatibility (*d'*, hit rate, correct rejection rate, and *v*), results consistently demonstrated the presence of CSE. Given that inhibition in one trial can affect subsequent trials and potentially influence our main findings, we excluded trials where the previous stimulus-task was incompatible and focused only on trials where the previous stimulus-task was compatible. Even under these conditions, we again found extremely strong evidence for impaired performance when inhibition was required (CI vs. CC).

Additionally, since the color-word congruency of the current stimulus could interact with CSE and influence the results, we also examined the three-way interaction between previous and current stimulus-task compatibility

and current stimulus color-word congruency. The results confirmed that CSE were present regardless of whether the current stimulus was incongruent or congruent. Moreover, the CSE was stronger when color-word congruency of the current stimulus was incongruent, suggesting that incongruent color-word congruency amplified CSE effects. These results highlight the necessity of controlling for the effects of CSE and current stimulus color-word congruency to ensure a more precise examination of the relationship between inhibition and updating. Thus, we controlled for the condition where the previous trial's stimulus-task compatibility was compatible and the current stimulus color-word was congruent. Even under these controlled conditions, we found extremely strong evidence for impaired performance when inhibition was required (CIc vs. CCc) in reaction time, accuracy, and non-decision time. Furthermore, after controlling the effects of the CSE and current stimulus color-word congruency, our task demonstrated an even larger effect size than traditional Stroop task, suggesting that we successfully manipulated inhibition within the updating task. Together, these findings strongly support the notion that inhibition and updating rely on shared cognitive resources (Fleming et al., 2016; Friedman et al., 2008; Ito et al., 2015; Löffler et al., 2024). Further support for this integrated cognitive framework comes from research by Löffler et al. (2024), who demonstrated that inhibition and updating are factors within a common executive function. This aligns with findings that inhibition is central to general executive functions predicting updating abilities (Fleming et al., 2016; Friedman et al., 2008, 2020; Ito et al., 2015). Updating, therefore, inherently involves inhibition, as it requires suppressing irrelevant information and removing outdated content from working memory (Zacks & Hasher, 1994). Recent studies, such as Yu et al. (2024), reinforce this view, showing that stimulating brain areas associated with inhibition through anodal transcranial direct current stimulation (tDCS) impaired performance in updating sub-processes. These findings challenge the traditional three-factor model of executive function, which separates inhibition and updating as distinct processes (Miyake et al., 2000). Instead, our results favor an alternative model in which inhibition serves as a general, higher-order executive control component, fundamentally intertwined with updating (Fleming et al., 2016; Friedman et al., 2008; Ito et al., 2015).

Moreover, the lower accuracy, longer reaction times, and smaller drift rates observed when inhibition was required compared to when only updating was needed confirm that DDM can effectively capture differences between conditions (Milosavljevic et al., 2010; Ratcliff & McKoon, 2008). The longer non-decision times observed in current incompatible stimulus-task trials reflect participants' inhibition of dominant judgement, demonstrating the validity of our experimental manipulation. Additionally, the HDDM model comparison revealed that including

previous stimulus-task compatibility significantly improved model fit compared to when it was excluded (Model 4 vs. Model 1). This finding suggested that the previous stimulus-task compatibility influenced both decision and non-decision processes, leading to CSE. Previous computational modeling studies have proposed that a key mechanism underlying the CSE is the reduced interference from task-irrelevant information following conflict trials (Koob et al., 2023; Luo & Proctor, 2022). Supporting this notion, our results showed that for a crucial parameter in our study—drift rate (*v*)—including previous trial's stimulus-task compatibility led to moderate evidence against an interaction between current stimulus-task compatibility and current stimulus color-word congruency. This suggests that whether inhibition was required in the previous trial modulates the extent to which task-irrelevant information influences evidence accumulation in the current trial. Besides, we observed an interaction between the congruency of the current stimulus-task compatibility and the current stimulus color-word congruency on non-decision times, indicating that the color-word congruency of the current stimulus affects participants' encoding during non-decision processes.

This study provides an in-depth examination of the cognitive mechanisms through which inhibition influences updating, offering empirical support for the simultaneous processing relationship between these two executive functions. It not only introduces a new perspective on how individuals update information while resisting interference but also establishes a robust task paradigm for manipulating inhibition within an updating task.

Despite yielding valuable results, this study has several limitations. First, although our findings support the existence of shared cognitive resources between inhibition and updating from both behavioral and cognitive computational perspectives, previous research has found both shared and distinct cognitive resources associated with these executive functions (Engelhardt et al., 2015; Fleming et al., 2016; Friedman et al., 2008, 2011; Miyake et al., 2000; Saylik et al., 2022). The distinct mechanisms underlying inhibition and updating warrant further investigation. Second, prior studies have suggested that the N-back task may also involve proactive inhibition, specifically in suppressing irrelevant working memory information and preventing irrelevant stimuli from entering working memory (Ecker et al., 2014; Elmers et al., 2024; Kessler, 2018). However, due to the limitations of N-back paradigm, our study could not examine how this form of proactive inhibition interacts with the inhibition manipulated in our experiment. Future research could employ paradigms such as the reference-back task to further explore these interactions (Rac-Lubashevsky & Kessler, 2016b, 2016a). This paradigm allows for the differentiation and

measurement of updating sub-processes (e.g., gate opening, gate closing, substitution, and updating mode), making it possible to investigate the inhibition inherent within the updating process (Nir-Cohen et al., 2023; Yu et al., 2024). Third, our task integrated congruent/incongruent Stroop task to create an overlap in the same/different judgement attributes within N-back task. While this approach successfully introduced inhibition, it also introduced semantic conflict, which may have influenced the results and introduced potential ambiguity. Future studies could consider using a spatially separated picture-word same/different judgment task to strengthen the judgement mapping while minimizing verbal interference.

In summary, this study employed an innovative experimental paradigm within a unified task framework, integrating signal detection theory and hierarchical drift diffusion modeling to demonstrate that inhibition and updating rely on share cognitive resources. These shared resources primarily influence discriminability, drift rate, and non-decision time. Although our task was potentially affected by the congruency sequence effect (CSE) and the color-word congruency of the current stimulus, the results remained robust even after controlling for these factors. At the same time, we found extremely strong Bayesian evidence that concurrent inhibition impairs updating performance, yielding a larger effect size than the traditional Stroop effect. These findings support the conceptualization of inhibition as a general higher-order executive control factor, challenging the traditional three-factor model that treats inhibition and updating as separate executive functions.

4. Data availability

Our raw data, analysis data, and HDDM code are accessible via the Open Science Framework: https://osf.io/t6fsu/.

References

Baddeley, A. (1996). Exploring the Central Executive. *The Quarterly Journal of Experimental Psychology Section A*, *49*(1), 5–28. https://doi.org/10.1080/713755608

Bissett, P. G., Eisenberg, I. W., Shim, S., Rios, J. A. H., Jones, H. M., Hagen, M. P., Enkavi, A. Z., Li, J. K., Mumford, J. A., MacKinnon, D. P., Marsch, L. A., & Poldrack, R. A. (2024). Cognitive tasks, anatomical MRI, and functional MRI data evaluating the construct of self-regulation. *Scientific Data*, *11*(1), 809. https://doi.org/10.1038/s41597-024-03636-y

Bompas, A., Sumner, P., & Hedge, C. (2024). Non-decision time: The Higgs Boson of decision. *Psychological Review*. https://doi.org/10.1037/rev0000487

Braem, S., Bugg, J. M., Schmidt, J. R., Crump, M. J. C., Weissman, D. H., Notebaert, W., & Egner, T. (2019). Measuring Adaptive Control in Conflict Tasks. *Trends in Cognitive Sciences*, *23*(9), 769–783. https://doi.org/10.1016/j.tics.2019.07.002

Chwiesko, C., Janecek, J., Doering, S., Hollearn, M., McMillan, L., Vandekerckhove, J., Lee, M. D., Ratcliff, R., & Yassa, M. A. (2023). Parsing memory and nonmemory contributions to age-related declines in mnemonic discrimination performance: A hierarchical Bayesian diffusion decision modeling approach. *Learning & Memory*, *30*(11), 296–309. https://doi.org/10.1101/lm.053838.123

Collette, F., Van Der Linden, M., Laureys, S., Delfiore, G., Degueldre, C., Luxen, A., & Salmon, E. (2005). Exploring the unity and diversity of the neural substrates of executive functioning. *Human Brain Mapping*, *25*(4), 409–423. https://doi.org/10.1002/hbm.20118

Colom, R., Abad, F. J., Quiroga, M. Á., Shih, P. C., & Flores-Mendoza, C. (2008). Working memory and intelligence are highly related constructs, but why? *Intelligence*, *36*(6), 584–606. https://doi.org/10.1016/j.intell.2008.01.002

Dawkins, L., Powell, J. H., West, R., Powell, J., & Pickering, A. (2007). A double-blind placebo-controlled experimental study of nicotine: II—Effects on response inhibition and executive functioning. *Psychopharmacology*, *190*(4), 457–467. https://doi.org/10.1007/s00213-006-0634-6

Del Missier, F., Mäntylä, T., & Bruine De Bruin, W. (2010). Executive functions in decision making: An individual differences approach. *Thinking & Reasoning*, *16*(2), 69–97. https://doi.org/10.1080/13546781003630117

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*, 135–168. https://doi.org/10.1146/annurev-psych-113011-143750

Draheim, C., Hicks, K. L., & Engle, R. W. (2016). Combining Reaction Time and Accuracy: The Relationship Between Working Memory Capacity and Task Switching as a Case Example. *Perspectives on Psychological Science*, *11*(1), 133–155. https://doi.org/10.1177/1745691615596990

Draheim, C., Mashburn, C. A., Martin, J. D., & Engle, R. W. (2019). Reaction time in differential and developmental research: A review and commentary on the problems and alternatives. *Psychological Bulletin*, *145*(5), 508–535. https://doi.org/10.1037/bul0000192

Draheim, C., Tsukahara, J. S., Martin, J. D., Mashburn, C. A., & Engle, R. W. (2021). A toolbox approach to improving the measurement of attention control. *Journal of Experimental Psychology: General*, *150*(2), 242–275. https://doi.org/10.1037/xge0000783

Duthoo, W., Abrahamse, E. L., Braem, S., Boehler, C. N., & Notebaert, W. (2014). The heterogeneous world of congruency sequence effects: An update. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.01001

Ecker, U. K. H., Lewandowsky, S., & Oberauer, K. (2014). Removal of information from working memory: A specific updating process. *Journal of Memory and Language*, *74*, 77–90. https://doi.org/10.1016/j.jml.2013.09.003

Egner, T. (2007). Congruency sequence effects and cognitive control. *Cognitive, Affective, & Behavioral Neuroscience*, *7*(4), 380–390. https://doi.org/10.3758/CABN.7.4.380

Egner, T., & Hirsch, J. (2005). Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information. *Nature Neuroscience*, *8*(12), 1784–1790. https://doi.org/10.1038/nn1594

Elmers, J., Yu, S., Talebi, N., Prochnow, A., & Beste, C. (2024). Neurophysiological effective network connectivity supports a threshold-dependent management of dynamic working memory gating. *iScience*, *27*(4), 109521. https://doi.org/10.1016/j.isci.2024.109521

Engelhardt, L. E., Briley, D. A., Mann, F. D., Harden, K. P., & Tucker-Drob, E. M. (2015). Genes Unite Executive Functions in Childhood. *Psychological Science*, *26*(8), 1151–1163. https://doi.org/10.1177/0956797615577209

Espy, K. A. (2004). Using Developmental, Cognitive, and Neuroscience Approaches to Understand Executive Control in Young Children. *Developmental Neuropsychology*, *26*(1), 379–384. https://doi.org/10.1207/s15326942dn2601_1

Fleming, K. A., Heintzelman, S. J., & Bartholow, B. D. (2016). Specifying Associations Between Conscientiousness and Executive Functioning: Mental Set Shifting, Not Prepotent Response Inhibition or Working Memory Updating. *Journal of Personality*, *84*(3), 348–360. https://doi.org/10.1111/jopy.12163

Forstmann, B. U., Ratcliff, R., & Wagenmakers, E.-J. (2016). Sequential Sampling Models in Cognitive Neuroscience: Advantages, Applications, and Extensions. *Annual Review of Psychology*, *67*(1), 641–666. https://doi.org/10.1146/annurev-psych-122414-033645

Frank, M. J., Gagne, C., Nyhus, E., Masters, S., Wiecki, T. V., Cavanagh, J. F., & Badre, D. (2015). fMRI and EEG Predictors of Dynamic Decision Parameters during Human Reinforcement Learning. *The Journal of Neuroscience*, *35*(2), 485–494. https://doi.org/10.1523/JNEUROSCI.2036-14.2015

Freis, S. M., Alexander, J. D., Anderson, J. E., Corley, R. P., De La Vega, A. I., Gustavson, D. E., Vrieze, S. I., & Friedman, N. P. (2024). Associations between executive functions assessed in different contexts in a genetically informative sample. *Journal of Experimental Psychology: General*, *153*(1), 70–85. https://doi.org/10.1037/xge0001471

Freis, S. M., Morrison, C. L., Lessem, J. M., Hewitt, J. K., & Friedman, N. P. (2022). Genetic and environmental influences on executive functions and intelligence in middle childhood. *Developmental Science*, *25*(1), e13150. https://doi.org/10.1111/desc.13150

Friedman, N. P., Hatoum, A. S., Gustavson, D. E., Corley, R. P., Hewitt, J. K., & Young, S. E. (2020). Executive Functions and Impulsivity Are Genetically Distinct and Independently Predict Psychopathology: Results From Two Adult Twin Studies. *Clinical Psychological Science*, *8*(3), 519–538. https://doi.org/10.1177/2167702619898814

Friedman, N. P., Miyake, A., Robinson, J. L., & Hewitt, J. K. (2011). Developmental trajectories in toddlers' self-restraint predict individual differences in executive functions 14 years later: A behavioral genetic analysis. *Developmental Psychology*, *47*(5), 1410–1430. https://doi.org/10.1037/a0023750

Friedman, N. P., Miyake, A., Young, S. E., DeFries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General*, *137*(2), 201–225. https://doi.org/10.1037/0096-3445.137.2.201

Frings, C., Hommel, B., Koch, I., Rothermund, K., Dignath, D., Giesen, C., Kiesel, A., Kunde, W., Mayr, S., Moeller, B., Möller, M., Pfister, R., & Philipp, A. (2020). Binding and Retrieval in Action Control (BRAC). *Trends in Cognitive Sciences*, *24*(5), 375–387. https://doi.org/10.1016/j.tics.2020.02.004

Gelman, A., Carlin, J. B., Stern, H. S., Vehtari, A., & Rubin, D. (2013). Bayesian data analysis, third edition. In *Bayesian Data Analysis, Third Edition*.

Godefroy, O., Cabaret, M., Petit-Chenal, V., Pruvo, J.-P., & Rousseaux, M. (1999). Control Functions of the Frontal Lobes. Modularity of the Central-Supervisory System? *Cortex*, *35*(1), 1–20. https://doi.org/10.1016/S0010-9452(08)70782-2

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics.* (pp. xi, 455). John Wiley.

Halsey, L. G. (2019). The reign of the *p* -value is over: What alternative analyses could we employ to fill the power vacuum? *Biology Letters*, *15*(5), 20190174. https://doi.org/10.1098/rsbl.2019.0174

Hedge, C., Powell, G., Bompas, A., & Sumner, P. (2022). Strategy and processing speed eclipse individual differences in control ability in conflict tasks. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *48*(10), 1448–1469. https://doi.org/10.1037/xlm0001028

Hedge, C., Powell, G., Bompas, A., Vivian-Griffiths, S., & Sumner, P. (2018). Low and variable correlation between reaction time costs and accuracy costs explained by accumulation models: Meta-analysis and simulations. *Psychological Bulletin*, *144*(11), 1200–1227. https://doi.org/10.1037/bul0000164

Heitz, R. P. (2014). The speed-accuracy tradeoff: History, physiology, methodology, and behavior. *Frontiers in Neuroscience*, *8*. https://doi.org/10.3389/fnins.2014.00150

Himi, S. A., Bühner, M., & Hilbert, S. (2021). Advancing the Understanding of the Factor Structure of Executive Functioning. *Journal of Intelligence*, *9*(1), 16. https://doi.org/10.3390/jintelligence9010016

Himi, S. A., Bühner, M., Schwaighofer, M., Klapetek, A., & Hilbert, S. (2019). Multitasking behavior and its related constructs: Executive functions, working memory capacity, relational integration, and divided attention. *Cognition*, *189*, 275–298. https://doi.org/10.1016/j.cognition.2019.04.010

Hockey, A., & Geffen, G. (2004). The concurrent validity and test?retest reliability of a visuospatial working memory task. *Intelligence*, *32*(6), 591–605. https://doi.org/10.1016/j.intell.2004.07.009

Holder, L. J., Prasad, A., Han, J., Torok, M., & Wong, Q. J. J. (2021). Shifting as a key executive function underlying cognitive restructuring for individuals with elevated social anxiety. *Psychology and Psychotherapy: Theory, Research and Practice*, *94*(2), 217–230. https://doi.org/10.1111/papt.12301

Ito, T. A., Friedman, N. P., Bartholow, B. D., Correll, J., Loersch, C., Altamirano, L. J., & Miyake, A. (2015). Toward a comprehensive understanding of executive cognitive function in implicit racial bias. *Journal of Personality and Social Psychology*, *108*(2), 187–218. https://doi.org/10.1037/a0038557

Jarosz, A. F., & Wiley, J. (2014). What Are the Odds? A Practical Guide to Computing and Reporting Bayes Factors. *The Journal of Problem Solving*, *7*(1). https://doi.org/10.7771/1932-6246.1167

JASP Team. (2024). *JASP (Version 0.19.3) [Computer software]*. https://jasp-stats.org/

Jeffreys, H. (1998). *Theory of probability* (3rd ed). Clarendon Press□; Oxford University Press.

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), 220–245. https://doi.org/10.1037/xge0000119

Jurado, M. B., & Rosselli, M. (2007). The Elusive Nature of Executive Functions: A Review of our Current Understanding. *Neuropsychology Review*, *17*(3), 213–233. https://doi.org/10.1007/s11065-007-9040-z

Kessler, Y. (2018). *N* –2 repetition leads to a cost within working memory and a benefit outside it. *Annals of the New York Academy of Sciences*, *1424*(1), 268–277. https://doi.org/10.1111/nyas.13607

Koob, V., Mackenzie, I., Ulrich, R., Leuthold, H., & Janczyk, M. (2023). The role of task-relevant and task-irrelevant information in congruency sequence effects: Applying the diffusion model for conflict tasks. *Cognitive Psychology*, *140*, 101528. https://doi.org/10.1016/j.cogpsych.2022.101528

Lavie, N. (2005). Distracted and confused?: Selective attention under load. *Trends in Cognitive Sciences*, *9*(2), 75–82. https://doi.org/10.1016/j.tics.2004.12.004

Lavie, N. (2010). Attention, Distraction, and Cognitive Control Under Load. *Current Directions in Psychological Science*, *19*(3), 143–148. https://doi.org/10.1177/0963721410370295

Lavie, N., Hirst, A., De Fockert, J. W., & Viding, E. (2004). Load Theory of Selective Attention and Cognitive Control. *Journal of Experimental Psychology: General*, *133*(3), 339–354. https://doi.org/10.1037/0096-3445.133.3.339

Layher, E., Dixit, A., & Miller, M. B. (2020). Who gives a criterion shift? A uniquely individualistic cognitive trait. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *46*(11), 2075–2105. https://doi.org/10.1037/xlm0000951

Lee, M. D., & Wagenmakers, E.-J. (2014). *Bayesian Cognitive Modeling: A Practical Course* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781139087759

Lerche, V., Von Krause, M., Voss, A., Frischkorn, G. T., Schubert, A.-L., & Hagemann, D. (2020). Diffusion modeling and intelligence: Drift rates show both domain-general and domain-specific relations with intelligence. *Journal of Experimental Psychology: General*, *149*(12), 2207–2249. https://doi.org/10.1037/xge0000774

Lerche, V., & Voss, A. (2017). Retest reliability of the parameters of the Ratcliff diffusion model. *Psychological Research*, *81*(3), 629–652. https://doi.org/10.1007/s00426-016-0770-5

Lerche, V., Voss, A., & Nagler, M. (2017). How many trials are required for parameter estimation in diffusion modeling? A comparison of different optimization criteria. *Behavior Research Methods*, *49*(2), 513–537. https://doi.org/10.3758/s13428-016-0740-2

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*, *88*(4), 1092–1114. https://doi.org/10.1007/s00426-023-01924-7

Luo, C., & Proctor, R. W. (2022). A diffusion model for the congruency sequence effect. *Psychonomic Bulletin & Review*, *29*(6), 2034–2051. https://doi.org/10.3758/s13423-022-02119-8

Mager, R., Bullinger, A. H., Brand, S., Schmidlin, M., Schärli, H., Müller-Spahn, F., Störmer, R., & Falkenstein, M. (2007). Age-related changes in cognitive conflict processing: An event-related potential study. *Neurobiology of Aging*, *28*(12), 1925–1935. https://doi.org/10.1016/j.neurobiolaging.2006.08.001

Makowski, D. (2018). The psycho Package: An Efficient and Publishing-Oriented Workflow for Psychological Science. *The Journal of Open Source Software*, *3*(22), 470. https://doi.org/10.21105/joss.00470

Maniscalco, B., & Lau, H. (2014). Signal Detection Theory Analysis of Type 1 and Type 2 Data: Meta-d′, Response-Specific Meta-d′, and the Unequal Variance SDT Model. In S. M. Fleming & C. D. Frith (Eds.), *The Cognitive Neuroscience of Metacognition* (pp. 25–66). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-45190-4_3

Martins, J. S., Bartholow, B. D., Cooper, M. L., Von Gunten, C. D., & Wood, P. K. (2018). Associations between executive functioning, affect-regulation drinking motives, and alcohol use and problems. *Psychology of Addictive Behaviors*, *32*(1), 16–28. https://doi.org/10.1037/adb0000324

Milosavljevic, M., Malmaud, J., Huth, A., Koch, C., & Rangel, A. (2010). The Drift Diffusion Model Can Account for the Accuracy and Reaction Time of Value-Based Choices Under High and Low Time Pressure. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1901533

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex “Frontal Lobe” Tasks: A Latent Variable Analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Myers, C. E., Interian, A., & Moustafa, A. A. (2022). A practical introduction to using the drift diffusion model of decision-making in cognitive psychology, neuroscience, and health sciences. *Frontiers in Psychology*, *13*, 1039172. https://doi.org/10.3389/fpsyg.2022.1039172

Niendam, T. A., Laird, A. R., Ray, K. L., Dean, Y. M., Glahn, D. C., & Carter, C. S. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(2), 241–268. https://doi.org/10.3758/s13415-011-0083-5

Nir-Cohen, G., Egner, T., & Kessler, Y. (2023). The Neural Correlates of Updating and Gating in Procedural Working Memory. *Journal of Cognitive Neuroscience*, *35*(6), 919–940. https://doi.org/10.1162/jocn_a_01988

Pan, W., Geng, H., Zhang, L., Fengler, A., Frank, M. J., Zhang, R.-Y., & Chuan-Peng, H. (2025). dockerHDDM: A User-Friendly Environment for Bayesian Hierarchical Drift-Diffusion Modeling. *Advances in Methods and Practices in Psychological Science*, *8*(1), 25152459241298700. https://doi.org/10.1177/25152459241298700

Rac-Lubashevsky, R., & Kessler, Y. (2016a). Decomposing the n-back task: An individual differences study using the reference-back paradigm. *Neuropsychologia*, *90*, 190–199. https://doi.org/10.1016/j.neuropsychologia.2016.07.013

Rac-Lubashevsky, R., & Kessler, Y. (2016b). Dissociating working memory updating and automatic updating: The reference-back paradigm. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *42*(6), 951–969. https://doi.org/10.1037/xlm0000219

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., & McKoon, G. (2008). The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. *Neural Computation*, *20*(4), 873–922. https://doi.org/10.1162/neco.2008.12-06-420

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model: Current Issues and History. *Trends in Cognitive Sciences*, *20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

Redick, T. S., & Lindsey, D. R. B. (2013). Complex span and n-back measures of working memory: A meta-analysis. *Psychonomic Bulletin & Review*, *20*(6), 1102–1113. https://doi.org/10.3758/s13423-013-0453-9

Rey-Mermet, A., Gade, M., Souza, A. S., Von Bastian, C. C., & Oberauer, K. (2019). Is executive control related to working memory capacity and fluid intelligence? *Journal of Experimental Psychology: General*, *148*(8), 1335–1372. https://doi.org/10.1037/xge0000593

Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, *56*(5), 356–374. https://doi.org/10.1016/j.jmp.2012.08.001

Saylik, R., Williams, A. L., Murphy, R. A., & Szameitat, A. J. (2022). Characterising the unity and diversity of executive functions in a within-subject fMRI study. *Scientific Reports*, *12*(1), 8182. https://doi.org/10.1038/s41598-022-11433-z

Schubert, A.-L., Frischkorn, G., Hagemann, D., & Voss, A. (2016). Trait Characteristics of Diffusion Model Parameters. *Journal of Intelligence*, *4*(3), 7. https://doi.org/10.3390/jintelligence4030007

Servant, M., & Evans, N. J. (2020). A diffusion model analysis of the effects of aging in the Flanker Task. *Psychology and Aging*, *35*(6), 831–849. https://doi.org/10.1037/pag0000546

Smolker, H. R., Friedman, N. P., Hewitt, J. K., & Banich, M. T. (2018). Neuroanatomical Correlates of the Unity and Diversity Model of Executive Function in Young Adults. *Frontiers in Human Neuroscience*, *12*, 283. https://doi.org/10.3389/fnhum.2018.00283

Speiger, M. L., Rothmaler, K., Liszkowski, U., Rakoczy, H., & Wiesmann, C. G. (2025). Evidence that altercentric biases in a continuous false belief task depend on highlighting the agent's belief. *Cognition*, *256*, 106055. https://doi.org/10.1016/j.cognition.2024.106055

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian Measures of Model Complexity and Fit. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *64*(4), 583–639. https://doi.org/10.1111/1467-9868.00353

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, *31*(1), 137–149. https://doi.org/10.3758/BF03207704

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, *18*(6), 643–662. https://doi.org/10.1037/h0054651

Van Doorn, J., Van Den Bergh, D., Böhm, U., Dablander, F., Derks, K., Draws, T., Etz, A., Evans, N. J., Gronau, Q. F., Haaf, J. M., Hinne, M., Kucharský, Š., Ly, A., Marsman, M., Matzke, D., Gupta, A. R. K. N., Sarafoglou, A., Stefan, A., Voelkel, J. G., & Wagenmakers, E.-J. (2021). The JASP guidelines for conducting and reporting a Bayesian analysis. *Psychonomic Bulletin & Review*, *28*(3), 813–826. https://doi.org/10.3758/s13423-020-01798-5

Von Bastian, C. C., Blais, C., Brewer, G. A., Gyurkovics, M., Hedge, C., Kałamała, P., Meier, M. E., Oberauer, K., Rey-Mermet, A., Rouder, J. N., Souza, A. S., Bartsch, L. M., Conway, A. R. A., Draheim, C., Engle, R. W., Friedman, N. P., Frischkorn, G. T., Gustavson, D. E., Koch, I., … Wiemers, E. A. (2020). *Advancing the understanding of individual differences in attentional control: Theoretical, methodological, and analytical considerations*. https://doi.org/10.31234/osf.io/x3b9k

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition*, *32*(7), 1206–1220. https://doi.org/10.3758/BF03196893

Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review*, *25*(1), 35–57. https://doi.org/10.3758/s13423-017-1343-3

Wei, H., Yao, Y., & Zhou, L. (2022). Concurrent working memory task increases or decreases the flanker-related N2 amplitude. *Frontiers in Psychology*, *13*, 962153. https://doi.org/10.3389/fpsyg.2022.962153

Wei, H., & Zhou, R. (2020). High working memory load impairs selective attention: EEG signatures. *Psychophysiology*, *57*(11), e13643. https://doi.org/10.1111/psyp.13643

Wetzels, R., Matzke, D., Lee, M. D., Rouder, J. N., Iverson, G. J., & Wagenmakers, E.-J. (2011). Statistical Evidence in Experimental Psychology: An Empirical Comparison Using 855 *t* Tests. *Perspectives on Psychological Science*, *6*(3), 291–298. https://doi.org/10.1177/1745691611406923

White, C. N., & Poldrack, R. A. (2014). Decomposing bias in different types of simple decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *40*(2), 385–398. https://doi.org/10.1037/a0034851

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. *Frontiers in Neuroinformatics*, *7*. https://doi.org/10.3389/fninf.2013.00014

Wodka, E. L., Simmonds, D. J., Mahone, E. M., & Mostofsky, S. H. (2009). Moderate variability in stimulus presentation improves motor response control. *Journal of Clinical and Experimental Neuropsychology*, *31*(4), 483–488. https://doi.org/10.1080/13803390802272036

Yu, S., Konjusha, A., Ziemssen, T., & Beste, C. (2024). Inhibitory control in WM gate-opening: Insights from alpha desynchronization and norepinephrine activity under atDCS stimulation. *NeuroImage*, *289*, 120541. https://doi.org/10.1016/j.neuroimage.2024.120541

Zacks, R. T., & Hasher, L. (1994). Directed ignoring: Inhibitory regulation of working memory. *Inhibitory Processes in Attention, Memory, and Language.*, 241–264.

Zurrón, M., Pouso, M., Lindín, M., Galdo, S., & Díaz, F. (2009). Event-Related Potentials with the Stroop colour-word task: Timing of semantic conflict. *International Journal of Psychophysiology*, *72*(3), 246–252. https://doi.org/10.1016/j.ijpsycho.2009.01.002

Appendix

Appendix Tables

Appendix Table 1 Descriptive Statistics for Behavior Data Presented As Mean (*SE*)

Behavioral Data	Previous Incompatible				Previous Compatible			
	Current Incompatible		Current Compatible		Current Incompatible		Current Compatible	
	Current Inc	Current Con	Current Inc	Current Con	Current Inc	Current Con	Current Inc	Current Con
Reaction Time	1016.95 (20.96)	1079.58 (20.02)	1289.01 (21.76)	1075.61 (24.62)	1211.36 (20.20)	1255.22 (21.04)	979.97 (18.29)	847.80 (17.61)
Accuracy	0.89 (0.01)	0.88 (0.02)	0.75 (0.02)	0.79 (0.01)	0.71 (0.02)	0.74 (0.02)	0.94 (0.01)	0.93 (0.01)

Appendix Table 2 Descriptive Statistics for Signal Detection Theory (SDT) Parameters Presented As Mean (*SE*)

SDT Parameters	Previous Incompatible	Previous Compatible

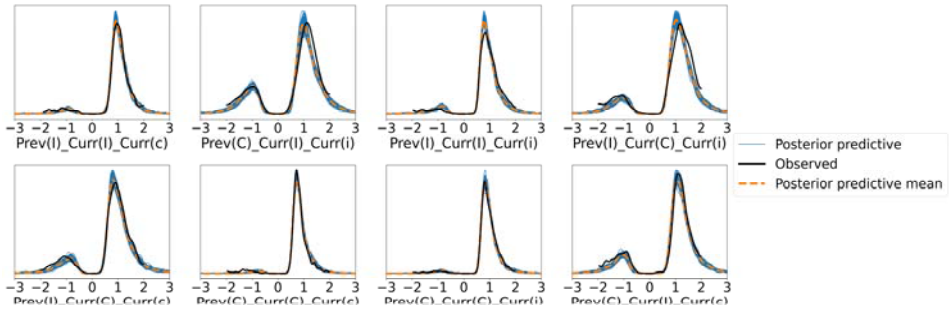
	Current Incompatible	Current Compatible	Current Incompatible	Current Compatible
Hit Rate	0.89 (0.01)	0.79 (0.01)	0.71 (0.02)	0.93 (0.01)
Correct Rejection	0.88 (0.02)	0.75 (0.02)	0.74 (0.02)	0.94 (0.01)
Perceptual Sensitivity (*d'*)	2.53 (0.12)	1.50 (0.07)	1.24 (0.09)	3.02 (0.09)
Criterion Shift (*c*)	-0.01 (0.02)	-0.04 (0.03)	0.05 (0.02)	0.09 (0.03)

Appendix Table 3 Descriptive Statistics for HDDM Parameters Drift Rate and Non-decision Time Presented As Mean (*SE*)

HDDM Parameters	Previous Incompatible				Previous Compatible			
	Current Incompatible		Current Compatible		Current Incompatible		Current Compatible	
	Current Inc	Current Con	Current Inc	Current Con	Current Inc	Current Con	Current Inc	Current Con
Drift Rate (v)	1.53 (0.05)	1.71 (0.05)	1.02 (0.04)	1.12 (0.03)	0.80 (0.04)	1.02 (0.05)	2.13 (0.05)	2.18 (0.05)
Non-decision Time (t)	0.56 (0.01)	0.68 (0.02)	0.71 (0.02)	0.53 (0.02)	0.80 (0.04)	0.75 (0.02)	0.60 (0.01)	0.48 (0.01)

Note: Non-decision time (*t*) is measured in seconds.

Appendix Figure



Appendix Figure 1: Posterior predictive check for the HDDM model 4. Blue line represent distributions of 100 randomly selected datasets generated from the posterior distribution of the model. Black line represent the distribution of observed data. Vertical axis represents probability density, and the horizontal axis represents RT (note, RT (seconds) for correct (error) responses are represented with positive (negative) values). The relative height of the negative and positive densities (divided by zero) in each panel reflects the accuracy for that condition.