Inhibition and Updating Share Common Resources: Evidence from 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 and examines whether this relationship is altered in individuals with trait anxiety. A novel paradigm that combines N-back and congruent/incongruent Stroop tasks were utilized to explore these issues by employing Signal Detection Theory (SDT) and the hierarchical drift diffusion model (HDDM) methods. The results revealed that participants exhibited longer response times and higher error rates in conditions requiring both inhibition and updating compared to those requiring updating alone. SDT analysis indicated lower discriminability, while HDDM analysis showed slower drift rates and longer non-decision times. These findings suggest that inhibition consumes cognitive resources, leading to worse updating performance, implying that both functions may rely on shared resources. In the anxiety group, higher trait anxiety scores correlated with increased response times and decreased accuracy. The drift rate fully mediated the effect of trait anxiety on accuracy, suggesting that the speed of effective information accumulation is a key mechanism underlying the abnormal functioning of inhibition and updating in individuals with anxiety. Overall, the results elucidate the relationship between these fundamental cognitive functions, supporting the notion that inhibition and updating share cognitive resources. Furthermore, this study provides evidence and insights into the cognitive abnormalities observed in individuals with anxiety.

Keywords: inhibition, updating, trait anxiety, drift diffusion model

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 utilize self-control 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 distinctiveness demonstrates that patients with damage to different brain regions exhibit contrasting performances in working memory and inhibition tasks, suggesting these functions may be governed by different neural substrates (Godefroy et al., 1999). Saylik et al. (2022) further specified particular brain regions for inhibition and updating: the left inferior frontal gyrus for inhibition, and the bilateral middle frontal gyrus and left supramarginal gyrus for updating. Conversely, other evidence suggests that the two processes may share common cognitive resources. Friedman et al. (2011) employed a set of independent tasks to measure inhibition and updating, revealing that inhibition and updating can be integrated into a single "Common Executive Function Factor" through latent variable analysis. Supporting this view, neuroimaging findings identify 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 the use of different measurement indicators for inhibition and updating when measured separately (Von Bastian et al., 2020). Experiments often use reaction time (RT) as an indicator of inhibition and accuracy as an indicator for updating (Del Missier et al., 2010; Himi et al., 2019, 2021; Martins et al., 2018; Friedman et al., 2008; Fleming et al., 2016). 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; Hedge 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 address these limitations, we have developed an innovative experimental paradigm that allows for the concurrent processing of response inhibition and updating. This paradigm combines the N-back task with the congruent/incongruent Stroop task. The N-back paradigm is a widely used approach for manipulating and assessing updating ability (Colom et al., 2008; Hockey & Geffen, 2004; Redick & Lindsey, 2013), and is designed to manipulate updating in our task. The congruent/incongruent Stroop task requires participants to judge whether the color and meaning of Chinese characters are congruent or incongruent (Dyer, 1973; Luo, 1999; Mager et al., 2007; Zurrón et al., 2009), involves consideration of both character meaning and semantics, without requiring inhibition of the automatic response to characters' meaning as in the conventional color-word Stroop task, and is used to assess congruency judgment for trigger response inhibition in N-back task. In our task, participants are required to determine whether the congruency between the current Chinese character's color and its meaning matches the previous character's congruency. Since participants first need to determine whether the color and meaning of the current Chinese character is congruent or incongruent, this allows us to control for participant's strategy effects on the experiment. After judging the congruency of the character's color and meaning, it will initiate either a "same" or "different" dominant response. When the previous stimulus is incongruent, the dominant response triggered by the stimulus differs from the correct response, thus requiring response inhibition. Conversely, when the previous stimulus is congruent, the dominant response aligns with the correct response, making response inhibition unnecessary. Thus, this task includes conditions that involve only updating and conditions that require both response inhibition and updating, enabling the measurement of concurrent processing (See **Figure 1** for details). The underlying principle of this paradigm is that if additional response inhibition impairs performance on the updating task, it would suggest that inhibition and updating share common cognitive resources.

This study employs Signal Detection Theory (SDT) and the hierarchical drift diffusion model (HDDM) to analyze the computational 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 (Ratcliff & McKoon, 2008; Ratcliff, 1978; Myers et al., 2022), 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: (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).

Among the parameters in the drift diffusion model (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, which would lead to a lower drift rate.

At the individual level, anxiety may influence the relationship between inhibition and updating. According to the Attentional Control Theory (ACT), heightened anxiety results in reduced attentional control (Berggren & Derakshan, 2013; Derakshan & Eysenck, 2009; Eysenck et al., 2007, 2023), disrupting top-down goal-driven processes (Pacheco-Unguetti et al., 2012), prompting the attentional

system to favor bottom-up/stimulus-driven processing, and impairing inhibitory function (Ansari & Derakshan, 2010, 2011; Berggren & Derakshan, 2013; Derakshan & Eysenck, 2009; Wright et al., 2014; Xia et al., 2020). Additionally, individuals with anxiety may also exhibit impairments in updating functions. For instance, I. Y et al. (2013) discovered that individuals with high anxiety displayed decreased processing efficiency in N-back tasks. However, it remains unclear whether anxiety impacts the relationship between inhibition and updating. Previous studies support the DDM's efficacy in identifying cognitive control impairments in individuals with anxiety (Han et al., 2023). Karalunas and Huang-Pollock (2013) investigated inhibition and working memory abnormalities in children with attention deficit hyperactivity disorder (ADHD). They discovered that children with ADHD exhibited lower drift rates (v), mediating the effects of ADHD on both inhibitory control and working memory capacity. This finding suggests that children with ADHD are less adept at inhibitory control and possess diminished working memory capacity. Regarding non-decision time (t), one study found that anxiety disorders had longer non-decision times for spatially incongruent threatening stimuli (Price et al., 2019). This finding suggests that task-irrelevant information might interfere with the perception encoding and motor response processes in individuals with anxiety. Thus, abnormalities in the relationship between inhibition and updating in individuals with anxiety may manifest as lower drift rates and longer non-decision times.

In conclusion, this study investigates whether inhibition and updating share cognitive resources and explores their relationship in individuals with trait anxiety, focusing on the underlying cognitive mechanisms. We propose two hypotheses: (1) inhibition and updating share cognitive resources, such that when inhibition is required, updating performance is impaired; (2) the relationship between inhibition and updating is abnormal in individuals with anxiety.

2. Materials and Method

2.1 Participants

A total of 895 university students were screened using the Chinese version of the Trait Anxiety Inventory (Shek, 1988). Based on the norm for Chinese university students (M = 43.31, SD = 9.20), students scoring more than one standard deviation above the norm (≥ 52) were classified into the trait anxiety group, while those scoring more than one standard deviation below the norm (≤ 34) were classified into the control group. From this screening, 70 right-handed participants (39 males, 31 females) were selected. The control group consisted of 20 males and 15 females, while the anxiety group included 20 males and 19 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 15 RMB after completing the experiment.

2.2 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 1280 × 720 pixels, resulting in a total of 16 (4 × 4) stimulus images. Based on the congruency types of adjacent trials, four categories were established: cc (both trials congruent), ci (previous congruent, current incongruent), ii (both trials incongruent), and ic (previous incongruent, current congruent). Response inhibition was required for trials following incongruent stimuli (ii, ic), but not for those following congruent stimuli (cc, ci) (**Figure 1 B**). The experiment consisted of 198 trials, including two non-response trials at the beginning of each block. Half of the trials (98) required inhibition, while the other half did not. The trial types were distributed as follows: 49 each for cc and ic, and 47 each for ci and ii. Stimuli were presented in a pseudo-random order to prevent repetition priming effects (Egner, 2007), ensuring that no consecutive identical stimuli were presented. Additionally, the correct response keys ("F" and "J") were balanced across trials (Egner & Hirsch, 2005).

2.3 Experimental Design

The experiment employed a mixed design with a 2 (Group: Anxiety vs. Control) × 2 (Previous Stimulus Type: Incongruent vs. Congruent) × 2 (Current Stimulus Type: Incongruent vs. Congruent) factorial structure. Group was a between-subjects variable, while the other factors were within-subjects variables. The dependent variables were reaction time and accuracy.

2.4 Experimental Procedure

Stimuli were presented using E-Prime 2.0 (Psychology Software Tools). Each trial began with a fixation cross "+" displayed in the center of the screen for 1500 ms, followed by a Chinese character. Participants were required to quickly and accurately judge whether the congruency of the current character's "color-word" relationship was the same as that of the last trial. They were instructed to press "J" with their left index finger for "same" and "F" with their right index finger for "different". Characters appeared for up to 2000 ms, followed by a blank screen for 900-1200 ms. The first trial of the block did not required a response (**Figure 1**).

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.

---Insert Figure 1 about here---

2.5 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 avoid the influence of erroneous responses on subsequent trials. Our data and code are available online (https://osf.io/t6fsu/).

2.5 SDT analysis

Signal detection analysis was conducted using the R package 'psych' (Makowski, 2018). Hits were defined as correct responses when the current and last stimulus types were same, while misses were incorrect responses under the same condition. False Alarms (FA) were defined as incorrect responses when the current stimulus type differed from the previous one, and Correct Rejections (CR) were correct responses in this situation. 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 (**Figure 2**). 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 compared conditions where the previous stimulus was incongruent versus congruent to investigate the influence of inhibition on updating.

---Insert Figure 2 about here---

2.5 HDDM analysis

Data modeling was conducted using the Python package HDDM (version 0.9.8) (Pan et al., 2022; Wiecki et al., 2013). Based on our experimental objectives and paradigm, we hypothesized that inhibition would affect the drift rate, decision threshold, and non-decision time of updating. We also assumed that the current stimulus might influence the non-decision time *t*, as the visual properties of the current stimulus (such as color and brightness) could affect perceptual processes (Bompas et al., 2024). Additionally, we hypothesized that trait anxiety would impact drift rate, decision threshold, and non-decision time. Given that the same/different responses were balanced in the experiment, we assumed a neutral starting point *z* for all models. We tested four models, as follows (**Table 1**):

Models 1 and 2 were baseline models without anxiety effects, while Models 3 and 4 were corresponding comprehensive models incorporating anxiety effects. In Model 1, we allowed drift rate (*v*), decision threshold (*a*), and non-decision time (*t*) to vary with the last stimulus type (Last_stim), exploring whether inhibition would affect the updating process. Model 2 additionally allowed non-decision time (*t*) to vary with the current stimulus type (Now_stim), examining whether the current stimulus would influence non-decision time *t*. Models 3 and 4 expanded on Models 1 and 2, respectively, by including group (anxiety vs. control) as a factor affecting drift rate, decision threshold, and non-decision time.

To ensure model convergence and data validity, trials with no response or reaction times below 200ms were excluded. 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 $R^{\wedge} < 1.1$ indicating good convergence. 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). All four models converged and were validated through posterior predictive checks of reaction times.

---Insert Table 1 about here---

3. Results

3.1 Behavioral results

For reaction times, the analysis of variance revealed a significant main effect of previous stimulus congruency ($F(1,68) = 75.43$, $p < .001$, $\eta^2 = 0.10$). Reaction times following incongruent stimuli ($M = 1129.63$, $SE = 17.38$) were significantly longer than those following congruent stimuli ($M = 1025.88$, $SE = 15.49$, $p < .001$). The main effect of current stimulus congruency was also significant ($F(1,68) = 35.04$, $p < .001$, $\eta^2 = 0.02$), with longer reaction times for incongruent current stimuli ($M = 1095.72$, $SE = 15.79$) compared to congruent ones ($M = 1052.48$, $SE = 15.36$, $p < .001$). The main effect of the group was not significant ($F(1,68) = 1.48$, $p = .228$, $\eta^2 = 0.01$). The three-way interaction between previous stimulus congruency, current stimulus congruency, and the group was not significant ($F(1,68) = 3.88$, $p = .053$, $\eta^2 = 0.003$). However, the interaction between previous and current stimulus congruency was significant ($F(1,68) = 131.02$, $p < .001$, $\eta^2 = 0.11$). For congruent current stimuli, reaction times were significantly longer when the previous stimulus was incongruent (ic: $M = 1162.83$, $SE = 18.14$)

compared to congruent (cc: M = 943.95, SE = 16.60, p < .001). For incongruent current stimuli, there was no significant difference in reaction times between previous incongruent (ii: M = 1095.29, SE = 19.35) and previous congruent trials (ci: M = 1162.83, SE = 18.14, p = .705).

Regarding accuracy, there was a significant main effect of previous stimulus congruency ($F(1,68) = 21.38$, $p < .001$, $\eta^2 = 0.04$), with lower accuracy following incongruent stimuli (M = .81, SE = .01) compared to congruent stimuli (M = .85, SE = .08, p < .001). The main effect of current stimulus congruency was not significant ($F(1,68) = 0.17$, $p = .682$, $\eta^2 = 0.002$). Neither the three-way interaction between previous stimulus congruency, current stimulus congruency, and group ($F(1,68) = 0.18$, $p = .670$, $\eta^2 = 0.004$), nor the two-way interaction between previous and current stimulus congruency ($F(1,68) = 0.19$, $p = .661$, $\eta^2 = 0.005$) were significant (Figure 3).

---Insert Figure 3 about here---

3.2 SDT results

The signal detection analysis indicated that the d' following an incongruent stimulus was significantly lower than when the previous stimulus was congruent (t = -4.761, p < .001; Figure 4). Additionally, there was a significantly higher false alarm rate (t = 4.845, p < .001) and a significantly lower hit rate (t = -4.845, p < .001) after incongruent stimuli. However, no significant difference was found in decision bias (c) between the two conditions (t = -1.225, p = .225; Table 2).

---Insert Figure 4 about here---

3.3 HDDM results

Based on the DIC and model comparison, HDDM revealed that Model 2 provided the best fit (see **Figure 5**). This suggests that the current stimulus congruency affects non-decision time (t), and trait

anxiety has no significant effect on the experimental parameters. Therefore, we selected Model 2 as the best-fitting model and proceeded with parameter analysis.

---Insert Figure 5 about here---

The results indicated that drift rate (v) was lower following an incongruent stimulus compared to a congruent stimulus ($P < 0.001$). Non-decision time (t) was analyzed using Bayesian repeated measures ANOVA. Based on previous guidelines for interpreting Bayes factors (Jarosz & Wiley, 2014; Jeffreys, 1961; Wetzels et al., 2011), the current data provide extremely strong evidence for the main effect of previous stimulus congruency ($BF_{incl}= \infty$). Post-hoc tests revealed extremely strong evidence that non-decision time was significantly longer after an incongruent stimulus compared to a congruent stimulus ($BF_{10}= 1.42\times10^{9}$). However, no significant difference was found in decision threshold (a) between trials following incongruent and congruent stimuli ($P = 0.88$) (**Figure 6**).

---Insert Figure 6 about here---

3.4 Correlation results

Correlation analyses were conducted between trait anxiety scores and both reaction times and accuracy rates for trials following either an incongruent or congruent stimulus, separately for the anxiety group and the control group. In the anxiety group, TAI scores were positively correlated with reaction times for both trials where the previous stimulus was incongruent ($r = 0.39$, $p = .030$) and congruent ($r = 0.45$, $p = .010$). TAI scores were negatively correlated with accuracy for both trials where the previous stimulus was incongruent ($r = -0.37$, $p = .039$) and congruent ($r = -0.43$, $p = .016$; Figure **7**). In the control group, no significant correlations were found between TAI scores and either reaction times or accuracy (all $Ps > .120$).

Additionally, to further investigate the impact of anxiety on inhibition and updating, we conducted a correlation analysis between drift rate and behavioral performance. Since hierarchical models tend to shrink individual-level parameters toward the group mean, which violates the independence assumption required for correlation analysis (see Liu et al., 2022 for a detailed explanation of this issue), we re-fit the

data for each participant using the non-hierarchical version of the best-fitting drift diffusion model. We then performed correlation analyses between drift rate and behavioral performance. The results showed that, even after controlling for state anxiety, TAI scores in the anxiety group were negatively correlated with drift rate for both trials where the previous stimulus was incongruent (r = -0.36, p = .049) and congruent (r = -0.46, p = .010), while no significant correlations were observed in the control group (all *Ps* > .528).

---Insert Figure 7 about here---

3.5 Mediation results

To explore the cognitive computational mechanisms underlying inhibition and updating in individuals with anxiety, we conducted a mediation analysis to examine the relationship between anxiety levels, computational parameters, and behavioral performance. As shown in Figure 6, drift rate was used as the independent variable, trait anxiety scores in the anxiety group were used as the predictor, behavioral performance was the dependent variable, and state anxiety was included as a control variable. A bootstrapping method with 2,000 samples was employed for the mediation analysis.

The results showed that, when the previous trial was congruent (only requiring updating), the indirect effect on reaction time was not significant ($a \times b$ = 5.57, SE = 0.13, 95%CI = [-0.11, 0.40]), indicating that drift rate did not significantly mediate the relationship between trait anxiety scores and updating reaction time in the anxiety group. However, the total effect on accuracy was significant (c = -0.01, SE = 0.01, 95% CI =[-0.02, -0.003]), while the direct effect was not (c' = -0.001, SE = 0.003, 95% CI = [-0.01, 0.004]). The indirect effect was significant ($a \times b$ = -0.01, SE = 0.16, 95% CI = [-0.77, -0.14]), suggesting that drift rate fully mediated the effect of trait anxiety on accuracy in conditions where only updating was required.

When the previous trial was incongruent (requiring both inhibition and updating), the indirect effect on reaction time was not significant ($a \times b$ = 4.59, SE = 0.12, 95% CI = [-0.16, 0.35]), indicating that drift rate did not significantly mediate the relationship between trait anxiety and reaction time in tasks

requiring both inhibition and updating. Similarly, the indirect effect on accuracy was not significant ($a \times b$ = -0.01, *SE* = 0.20, 95% CI = [-0.75, 0.05]). However, the path from the predictor to the mediator was significant (a = -0.06, *SE* = 0.03, 95% CI = [-0.11, -0.00]), and the path from the mediator to the outcome was also significant (b = 0.23, *SE* = 0.02, 95% CI = [0.19, 0.27]). This suggests that drift rate fully mediated the effect of trait anxiety on accuracy in conditions requiring both inhibition and updating in the anxiety group (Figure 8).

---Insert Figure 8 about here---

4. Discussion

This study examined the relationship between inhibition and updating and whether this relationship is abnormal in individuals with anxiety. Utilizing an innovative paradigm, signal detection theory, and a HDDM, we found that concurrent processing of inhibition and updating impairs performance on the updating task, suggesting that inhibition and updating share cognitive resources. Through correlation and mediation effect tests in the anxiety group, we discovered that increased trait anxiety levels in individuals with trait anxiety are associated with poorer inhibition and updating abilities. Furthermore, the speed of information accumulation fully mediated the decline in accuracy, indicating that a slower speed of effective information accumulation is one of the reasons for the abnormal relationship between inhibition and updating in individuals with anxiety.

The findings support Hypothesis 1, positing that inhibition and updating share cognitive resources. This conclusion is substantiated by both behavioral and model-based results. Behaviorally, incongruent previous trial stimuli resulted in increased reaction times and error rates, indicating resource competition between inhibition and updating. Signal detection analysis further revealed a significant decline in participants' discriminability (d') when inhibition was necessary, suggesting a depletion of cognitive resources normally allocated to updating, weakening the ability to differentiate stimuli. Complementing these findings, the HDDM analysis showed a significant decrease in drift rate when inhibition was

required, evidencing a reduced speed of evidence accumulation in updating tasks. Together, these results underscore the shared cognitive resources between inhibition and updating (K. A. 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 (K. A. Fleming et al., 2016; Friedman et al., 2008, 2020; Ito et al., 2015). Updating, therefore, involves inhibition processes, as it necessitates suppressing irrelevant information and removing outdated data from working memory (Zacks & Hasher, 1994). Recent studies, such as S. 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 (Miyake et al., 2000). In contrast, our results favor a model recognizing inhibition as a general, higher-order executive control component (K. A. Fleming et al., 2016; Friedman et al., 2008; Ito et al., 2015).

Furthermore, 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 when the previous stimulus was incongruent reflect participants' inhibition of dominant responses, demonstrating the validity of our experimental manipulation. Moreover, the HDDM model comparison revealed that including the current stimulus color-word congruency significantly improved model fit compared to when it was excluded (Model 2 vs. Model 1). This suggests that the color-word congruency of the current stimulus influences non-decision processes, this result consistent with the behavioral results. Additionally, we also observed an interaction between the congruency of the previous stimulus and the current stimulus on reaction times, indicating that the color-word congruency of the current stimulus affects participants' encoding during non-decision processes. However, no significant difference was found in the decision threshold between conditions requiring

inhibition and those not requiring inhibition. This suggests that the need for inhibition does not modulate participants' decision thresholds, aligning with findings from numerous studies (Han et al., 2023; Weigard et al., 2020).

The results affirm Hypothesis 2, which posits an altered relationship between inhibition and updating in individuals with anxiety. Specifically, in the anxiety group, higher trait anxiety scores were associated with longer reaction times and lower accuracy across both congruent and incongruent stimuli from the prior trial. This indicates that elevated anxiety levels are linked to diminished inhibition and updating capabilities. Furthermore, drift rate fully mediated the impact of increased trait anxiety scores on reduced accuracy, suggesting that slower evidence accumulation rate is a key mechanism contributing to cognitive deficits in anxious individuals (Adrover-Roig et al., 2023). This finding corroborates previous research indicating that heightened anxiety impairs both reaction time and accuracy in inhibition and updating tasks (Pelegrina et al., 2020; Y. Yu et al., 2018).

Our study intriguingly found no significant differences in cognitive performance between the anxiety and control groups. HDDM comparisons indicated that differentiating participants by anxiety levels did not enhance model fit (Model 4 vs. Model 2). This suggests that although performance may decline with increasing anxiety, overall performance remains comparable between high and low-anxiety individuals. We propose three explanations for this: (1) Compensatory Mechanisms: Anxious individuals might engage compensatory strategies, allocating additional cognitive resources to counteract anxiety's adverse effects (Eysenck et al., 2023). Yu et al. (2018) demonstrated that while task performance between high and low-anxiety individuals remained similar, high-anxiety participants exhibited increased N2 amplitudes, indicating enhanced activation to manage conflict stimuli. (2) Working Memory Load: A significant working memory load may be necessary to observe impaired updating abilities in anxious individuals. I. Y (2013) noted reaction time differences between high and low-anxiety groups under demanding 2-back and 3-back conditions, but not in simpler 1-back tasks. Qi et al. (2014) further supports that high working memory demands impair the ability of anxious individuals to filter distractors. (3) Anxiety Severity: The severity of anxiety could influence cognitive control capabilities (Beaudreau &

O'Hara, 2008; Zainal & Newman, 2022). Our study's reliance on self-reported anxiety may not capture the deficits associated with clinical anxiety. Studies have shown that individuals with clinical anxiety exhibit reduced working memory capacity compared to those with milder anxiety (Nyberg et al., 2021). Additionally, Yu et al. (2018) found significant differences in inhibition between clinically anxious individuals and those with self-reported anxiety, suggesting that anxiety levels distinctly affect cognitive performance. These findings highlight the nuanced relationship between anxiety and cognitive control, indicating the need for future research to account for compensatory strategies, task load, and anxiety severity.

This study provides an in-depth examination of the cognitive mechanisms by which inhibition affects updating, offering paradigm support for the synchronous processing relationship between these two cognitive functions. It presents a new perspective for understanding how individuals update information while resisting interference. At the individual differences level, the study highlights the significant impact of the information accumulation rate on cognitive accuracy in anxious individuals, offering important insights into the cognitive abnormalities experienced by this population.

Despite yielding valuable results, this study has several limitations. First, although our findings support the existence of shared mechanisms between inhibition and updating from both behavioral and cognitive computational perspectives, previous research have found both shared and distinct cognitive resources associated with these executive functions (Engelhardt et al., 2015; K. A. 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, our study utilized a sample of healthy individuals with varying levels of trait anxiety, rather than including participants with clinical anxiety or other anxiety-related disorders. Consequently, the observed relationship between inhibition and updating in anxious individuals requires further verification across a broader spectrum of anxiety and related mental disorders. Finally, this study relied primarily on behavioral experiments to explore the relationship between inhibition and updating. As a result, the specific mechanisms—particularly the neural substrates

involved—remain unclear. Future research should employ cognitive neuroscience methods to provide direct evidence for the shared or specific neural bases of inhibition and updating in various anxious populations.

In summary, this study utilized an innovative experimental paradigm along with cognitive computational modeling to demonstrate that inhibition and updating share cognitive resources, which are primarily influenced by drift rate and non-decisional time. Additionally, drift rate fully mediated the effects of anxiety and inhibition on updating accuracy. This suggests that a decrease in information accumulation speed may contribute to the abnormal relationship between inhibition and updating in anxious individuals. Our findings support the perspective of inhibition as a general higher-order executive control factor, which challenges the three-factor separation model of executive function. Furthermore, this research is significant for understanding the relationship between inhibition and updating, as well as the cognitive abnormalities observed in individuals with anxiety.

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Table 1

Summary of Hierarchical Drift Diffusion Models.

Model	Model structure	DIC
Model 1	Last_stim{*v* (l), *a* (l), *t* (l)}, Now_stim{none}, Group{none}	17230.70
Model 2	Last_stim{*v* (l), *a* (l), *t* (l)}, Now_stim{*t* (n)}, Group{none}	15707.60
Model 3	Last_stim{*v* (l), *a* (l), *t* (l)}, Now_stim{none}, Group{*v* (g), *a* (g), *t* (g)}	17231.97
Model 4	Last_stim{*v* (l), *a* (l), *t* (l)}, Now_stim{*t* (n)}, Group{*v* (g), *a* (g), *t* (g)}	15711.18

Note: Models of different complexity (number of hierarchical levels (l: Last_stim, n: Now_stim, g: Group) and permitted variation of model parameters (*a*: Decision Threshold, *t*: Non-decision time, *v*: Drift-rate) across these levels) that were fitted to the data and their Deviance Information Criterions (DICs). Based on the lowest DIC, Model 2 was chosen for analysis.

Table 2

Descriptive Statistics for Signal Detection Theory Parameters

SDT Parameters	Last Inc	Last Con	*t* Test	*p* Value

False alarms	0.160(0.013)	0.112(0.012)	$t = 4.845$	<.001
Hit rate	0.840(0.011)	0.882(0.008)	$t = -3.087$	= .003
Perceptual sensitivity (*d'*)	2.07(0.089)	2.43(0.06)	$t = -4.761$	<.001
Criterion shift (*c*)	0.007(0.02)	0.043(0.03)	$t = -1.225$	= .225

Note: Values are presented as mean (SD).

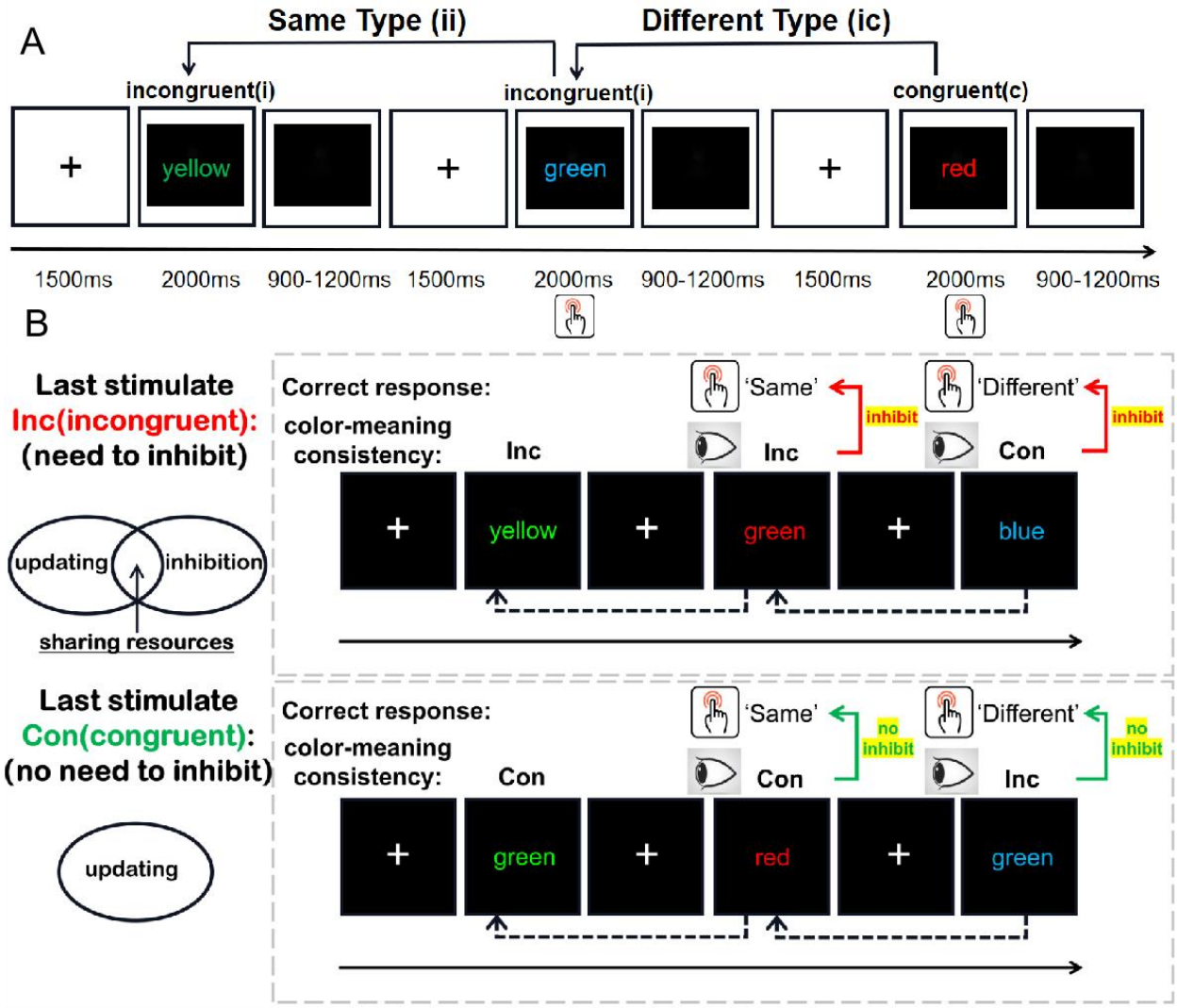

Figure 1. Experimental Procedure. (A) In each trial, a colored Chinese character is presented(Here we present the English rather than the Chinese version), where the color and its meaning are either congruent or incongruent. Participants were instructed to judge whether the current character's "color-word" congruency matched that of the previous trial. (B) This paradigm used the previous trial's color-word congruency to determine whether response inhibition was required: (1) **When the previous trial was incongruent**, the congruency category of the current trial and the correct key response were different. This mismatch triggered an erroneous dominant response, requiring inhibition to cancel it. For example, if the previous trial was incongruent and the current trial is congruent (ic): The correct key response is "different", but the current trail triggers a dominant "same" response, requiring inhibition to cancel the erroneous dominant response. If both the previous and current trials are incongruent (ii), the correct key response is "same", but the current trail triggers a dominant "different" response, again requiring inhibition. (2) **When the previous trial was congruent**, the congruency of the current trial and the correct key response was the same, meaning no inhibition was required, allowing the focus to updating. For example: If both the previous and current trials

were congruent (cc), the correct key response is “same”, matching the current trial’s congruency, so no inhibition is needed. If the previous trial was congruent and the current trial is incongruent (ci), the correct key response is “different”, and it matches the current trial's congruency, so no inhibition is required.

Last Inc	Respond “Same”	Respond “Different”
Now Stimulate: Inc	Hit (ii)	Miss (ii)
Now Stimulate: Con	False alarm (ic)	Correct reject (ic)

Last Con	Respond “Same”	Respond “Different”
Now Stimulate: Inc	False alarm (ci)	Correct reject (ci)
Now Stimulate: Con	Hit (cc)	Miss (cc)

Figure 2. Signal Detection Theory Classification Diagram. In this diagram, green represents correct responses, and red represents incorrect responses.

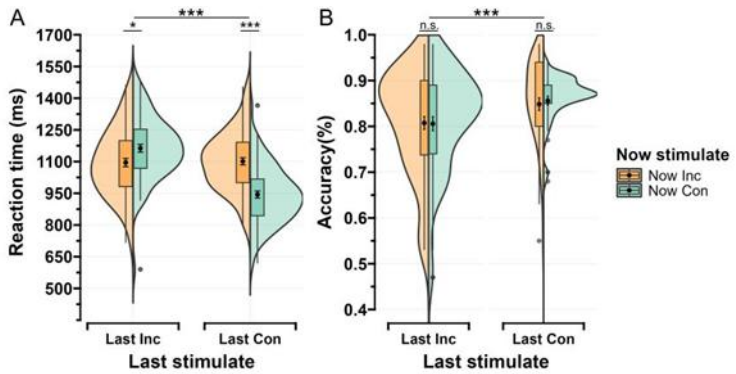

Figure 3. Behavioral Results. In each box-split violin plot, the midpoint of the box plot represents the mean of the data. The error bars around the midpoint represent the Standard Error of the Mean (SEM). The upper and lower limits of the box represent the third quartile (Q3, 75th percentile) and first 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. (A) Box-split violin plot of reaction time. (B) Box-split violin plot of accuracy. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

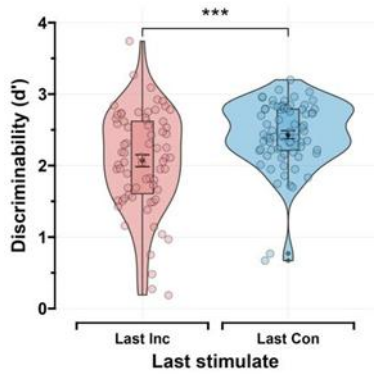

Figure 4. Signal Detection Analysis Diagram and Discriminability (*d*'), Results Significance levels: Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

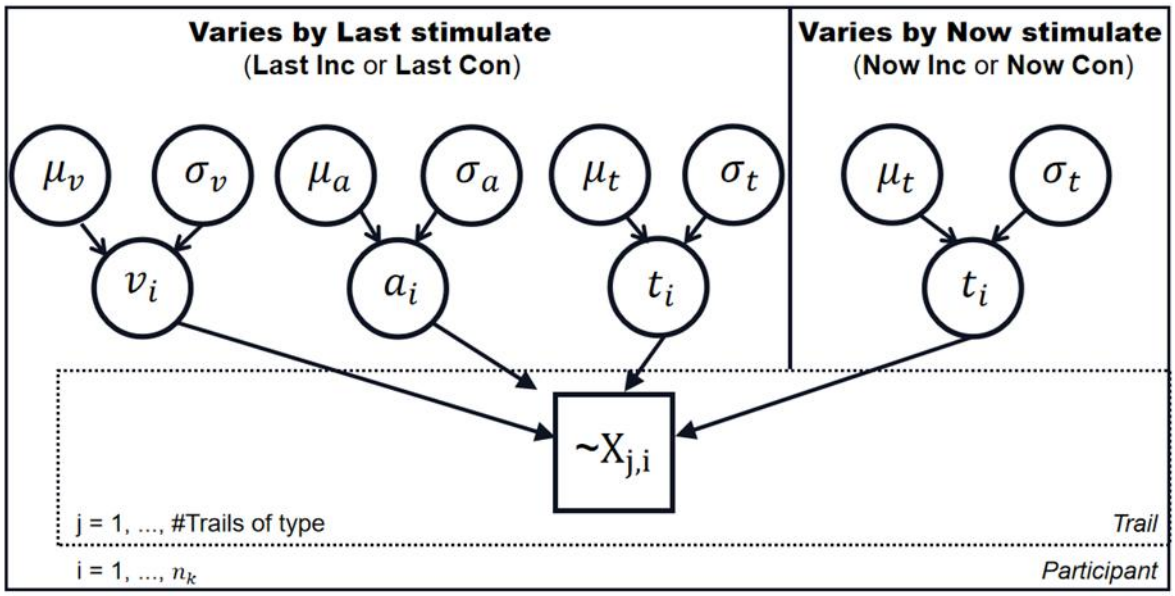

Figure 5. Diagram of the best fitting hierarchical drift diffusion model (HDDM) to the distribution of participant responses across trials (~Xi,j). The best fitting hierarchical HDDM permitted the rate of

evidence accumulation, decision threshold, and no decision time to vary by trial type (ie, 1 of each parameter for Last Inc or Last Con and no decision time with Now Inc and Now Con specially.)

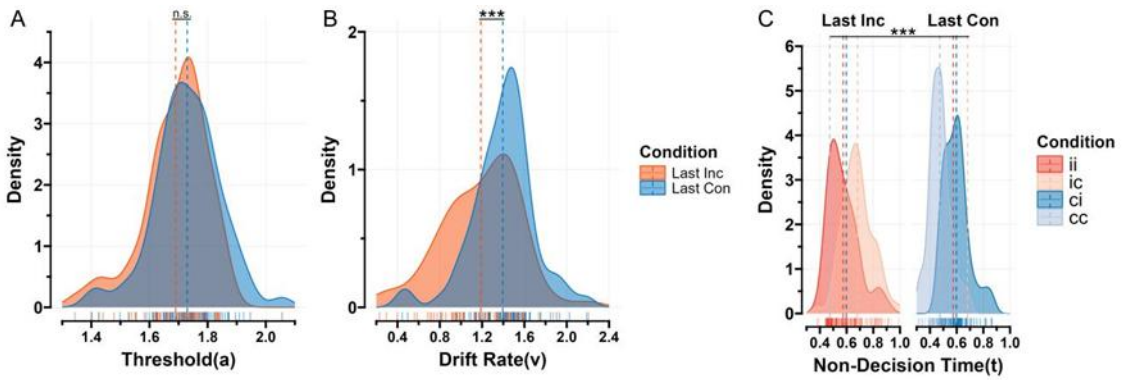

Figure 6. Group-level Results of Drift Diffusion Model Parameters. (A) Decision Threshold (*a*): No significant effect when previous trial was incongruent. (B) Drift Rate (*v*): The drift rate was significantly lower when the previous trial was incongruent. (C) Non-decision Time (*t*): The non-decision time was significantly lower when the previous trial was incongruent

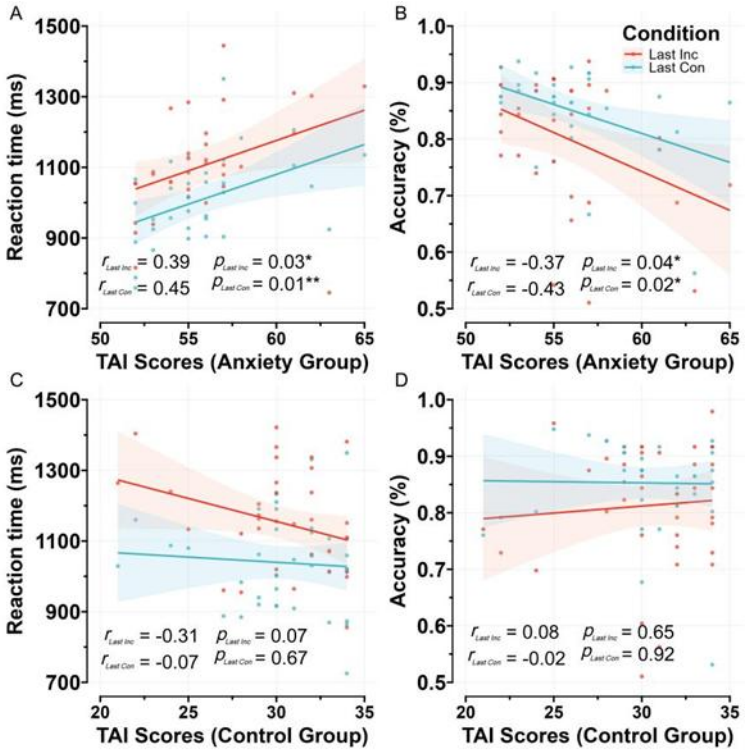

Figure 7. Correlation between Trait Anxiety Inventory (TAI) Scores, Reaction Time (RT) and Accuracy (ACC) in the Anxiety Group and Control Group. The figure illustrates the association between TAI scores and RT across two conditions: “Last Inc” (Last Incongruent) and “Last Con”(Last Congruent). TAI scores represent the trait anxiety level of participants, with higher scores indicating greater trait anxiety. The solid lines show linear regression fits, with shaded areas representing 95% confidence intervals. Data points are color-coded by condition, highlighting differences in RT as a function of anxiety level and task condition.(A) Correlation between TAI scores and RT in anxiety group. (B) Correlation between TAI scores and ACC in anxiety group. (C) Correlation between TAI scores and RT in control group. (D) Correlation between TAI scores and ACC in control group.

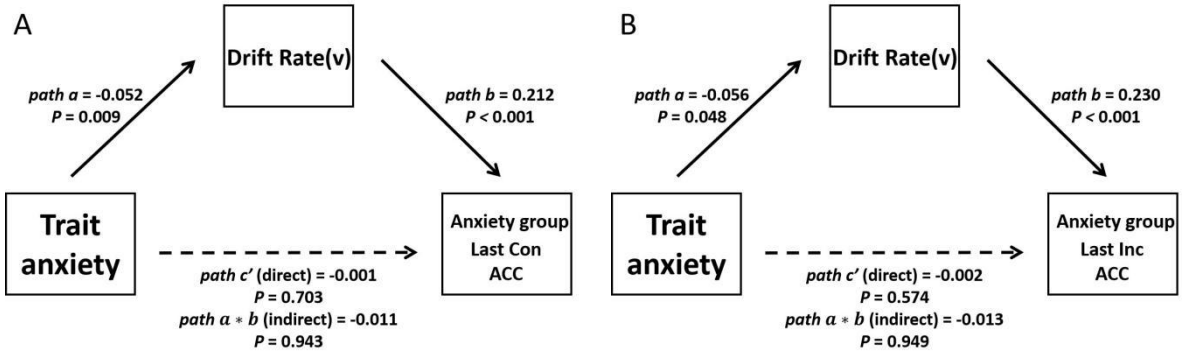

Figure 8. Mediation effect diagram. Drift rate completely mediated the effect of trait anxiety score on accuracy in anxiety group. (A) Drift rate completely mediated the effect of TAI scores on accuracy when previous stimulate was congruent in anxiety group. (B) Drift rate completely mediated the effect of TAI scores on accuracy when previous stimulate was incongruent in anxiety group.