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Task Conflict and Proactive Control: A Computational Theory of the Stroop Task

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The Stroop task is a central experimental paradigm used to probe cognitive control by measuring the ability of participants to selectively attend to task-relevant information and inhibit automatic task-irrelevant responses. Research has revealed variability in both experimental manipulations and individual differences. Here, we focus on a particular source of Stroop variability, the reverse-facilitation (RF; faster responses to nonword neutral stimuli than to congruent stimuli), which has recently been suggested as a signature of task conflict. We first review the literature that shows RF variability in the Stroop task, both with regard to experimental manipulations and to individual differences. We suggest that task conflict variability can be understood as resulting from the degree of proactive control that subjects recruit in advance of the Stroop stimulus. When the proactive control is high, task conflict does not arise (or is resolved very quickly), resulting in regular Stroop facilitation. When proactive control is low, task conflict emerges, leading to a slow-down in congruent and incongruent (but not in neutral) trials and thus to Stroop RF. To support this suggestion, we present a computational model of the Stroop task, which includes the resolution of task conflict and its modulation by proactive control. Results show that our model (a) accounts for the variability in Stroop-RF reported in the experimental literature, and (b) solves a challenge to previous Stroop models—their ability to account for reaction time distributional properties. Finally, we discuss theoretical implications to Stroop measures and control deficits observed in some psychopathologies.

Keywords: Stroop task, reverse facilitation, cognitive control, executive functions, computational model

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Cognitive control is an important human capacity that allows us to flexibly respond to the environment in a goal-relevant way, freeing us from the constraints of automaticity or stimulus bound. For example, in the Stroop task (MacLeod, 1991; Stroop, 1935), people are asked to respond to the font color of a color word (e.g., respond "blue," for the word *RED* presented in blue font) and ignore the automatic and task-irrelevant response (e.g., "red"). This ability to selectively attend to the goal-relevant dimensions of stimuli in our environment is crucial for adaptive and flexible behavior. The mechanism that mediates this control process was

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subject to intensive study in the last 30 years. An influential theoretical framework contends that control is achieved by a frontal brain mechanism that provides top–down bias to the bottom–up stream of information processing that links stimuli to their associated responses (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Cohen, Dunbar, & McClelland, 1990; Miller & Cohen, 2001). Although this framework is successful in accounting for an impressive amount of data, one of its challenges is to account for the marked variability in cognitive control with task contingencies and for the variability in control and selective-attention capacity among individuals.

Recently, a dual-mechanism control (DMC) framework that rises to this challenge was proposed by Braver (2012; see also De Pisapia & Braver, 2006). According to the DMC, much of the variability in attentional control is due to the balance between two types of control processes: a proactive process that is deployed in advance of the stimulus (e.g., pay attention to color and ignore the word) and a reactive process that is deployed after the stimulus is processed and triggers some type of conflict (I see the word *RED* in blue font color, but I need to respond to the color, so it is “blue”;
F1 see Braver, 2012, Figure 1). As Braver discusses in his review, this account explains aspects of control variability in a series of behavioral and imaging studies.

The first aim of this article is to review a source of control variability in the Stroop task, which was somewhat neglected in the literature: the Stroop facilitation. We focus on the Stroop task because it is the paradigmatic and most frequently employed control task (Eidels, Townsend, & Algom, 2010), and its underlying mechanism was computationally characterized (Botvinick et al., 2001; Cohen et al., 1990; Cohen & Huston, 1994). As we will show, the Stroop facilitation—the difference in response time (RT) between Stroop congruent (e.g., RED written in red) and Stroop nonword neutral stimuli (e.g., *XXXX* written in red) varies both with experimental contingencies and with individual differences and it indicates the presence of a somewhat neglected type of conflict in the Stroop task: the *task-conflict*. Our second aim is to develop an explicit computational model of the Stroop task, which extends the DMC framework, to account for control variability that involves task conflict. As we will show, the model also accounts for aspects of Stroop data (RT-variance) that were challenging in previous Stroop models (Mewhort, Braun, & Heathcote, 1992) and it exhibits dissociations between Stroop components (facilitation vs. interference; see next section), which have important implications in understanding control deficits in a number of pathologies.

The article is organized as follows. We start with a review of the recent literature on Stroop task conflict and highlight two sources of variability in Stroop facilitation: (a) within-subject variability as a function of task contingencies and (b) between-subjects variability that involves individual differences. We then introduce our model and show how it accounts for these two sources of variability and for properties of RT-distributions (variance). Finally, we discuss the implications for understanding group differences and performance in clinical populations.

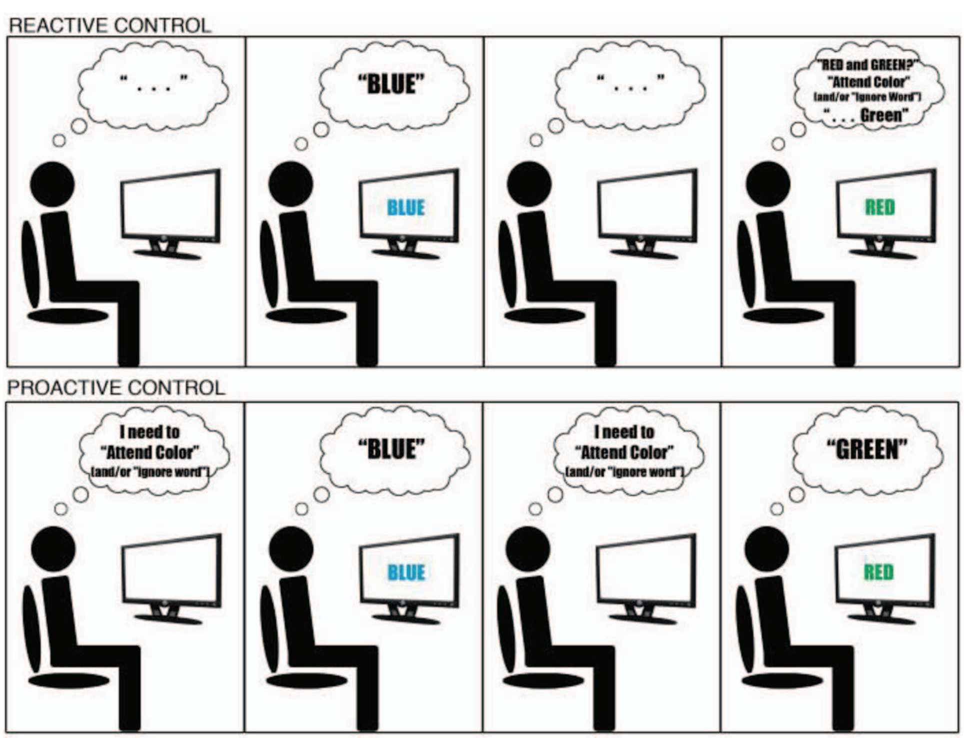

Figure 1. A schematic illustration of proactive and reactive control. From “The Variable Nature of Cognitive Control: A Dual Mechanisms Framework,” by T. S. Braver, 2012, *Trends in Cognitive Sciences, 16,* p. 107. Copyright 2014 by Elsevier Ltd. Reprinted with permission from Elsevier. See the online article for the color version of this figure.

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Task Conflict and Stroop Reverse Facilitation

The Stroop task is the classical tool for the study of attentional control and selectivity of attention (and its failure) in the laboratory. The task calls for responding to the relevant dimension (the font color) while ignoring or inhibiting irrelevant, but automatically processed, properties of the stimulus (the meaning of the printed word). The typical Stroop data shows a robust Stroop interference effect (i.e., RTs are slower for incongruent compared with neutral Stroop stimuli) and a smaller and less robust Stroop facilitation effect (i.e., RTs are slower for neutral compared with congruent Stroop stimuli). The robust Stroop interference effect indicates the presence of informational conflict. Despite the deployment of attention to color, the task-irrelevant information is also processed creating informational conflict. However, a different type of conflict, the task conflict, which is related to the less robust facilitation effect, has been less scrutinized. One reason for this is that RT for Stroop congruent stimuli—a type of stimuli for which there is no informational conflict but where a potential task conflict exists between reading the word and naming the color—is generally faster than for Stroop neutral stimuli. Thus, task conflict is not apparent in standard Stroop conditions. However, a number of neuroimaging studies showed that the anterior cingulate cortex (ACC)—a brain area thought to monitor conflict (Botvinick et al., 2001; Botvinick, Nystrom, Fissell, Carter, & Cohen, 1999; Braver, Barch, Gray, Molfese, & Snyder, 2001; Carter, Botvinick, & Cohen, 1999; Carter et al., 1998)—is more active, not only when contrasting incongruent Stroop trials to neutral trials, but also when contrasting congruent trials to neutral trials (e.g., Aarts, Roelofs, & van Turennout, 2009; Bench et al., 1993; Carter, Mintun, & Cohen, 1995; Roelofs, Van Turennout, & Coles, 2006; for older participants, see Milham et al., 2002). Thus, there seems to be inconsistencies between the neuroimaging findings indicating conflict in congruent trials and behavioral findings indicating that congruent trials are easier (and faster) than neutrals.

Recently, a number of studies from our group (Goldfarb & Henik, 2007; Kalanthroff, Avnit, Henik, Davelaar, & Usher, 2015; Kalanthroff, Goldfarb, & Henik, 2013; Kalanthroff, Goldfarb, Usher, & Henik, 2013; Kalanthroff & Henik, 2013, 2014) and others (e.g., Braverman & Meiran, 2010, 2015; Haggard, 2008; La Heij & Boelens, 2011; La Heij, Boelens, & Kuipers, 2010; Parris, 2014; Steinhauser & Hübner, 2009) reported that under specific conditions one can observe the task conflict, which is differentiable from the informational conflict (Aarts et al., 2009; Braverman, Berger, & Meiran, 2014). Specifically, an intriguing Stroop reverse facilitation (RF; slower RT to Stroop congruent compared with Stroop neutral trials) has been observed. It is important to note that the RF effect was only observed in conditions in which a nonword neutral was used but not when a noncolor word was used as neutral (e.g., Goldfarb & Henik, 2007; Kalanthroff, Anholt, Keren, & Henik, 2013; Kalanthroff & Henik, 2014). This supports the presence of an additional source of conflict in the Stroop task besides the informational conflict between the incongruent word (e.g., RED) and font color (e.g., blue), that is, the task conflict between the relevant color naming task and the irrelevant word reading task. The idea is that in both Stroop congruent and incongruent, but not in nonword neutral trials, the participant faces task conflict—should they name the font color or read the word?

The underlying idea to understanding task conflict is that a stimulus may trigger a response that has acquired a strong association with it (Allport & Wylie, 2000; Rogers & Monsell, 1995; Waszak, Hommel, & Allport, 2003). As proposed by Monsell (2003), task sets can be activated either by deliberate intentions that are governed by goals (i.e., endogenously) or by the perception of a stimulus attribute that is strongly associated with a particular task set (i.e., exogenously). This is consistent with the theory of *affordances*, which suggests that stimuli can trigger motor codes of specific behaviors, possibly even unconsciously, if they afford the opportunity for that organism to perform an action (Cisek, 2006; Gibson, 1979; Makris, Hadar, & Yarrow, 2011). For example, words trigger an automatic tendency to read (MacLeod & MacDonald, 2000; Rogers & Monsell, 1995)—the Stroop effect indicates that reading, either out loud or silently is a task strongly associated by the presence of words. Thus, while in Stroop incongruent trials the informational and the task conflict add up, leading to a robust RT slowing, in Stroop congruent trials, they go in opposite directions, resulting in Stroop facilitation effects with marked variability that sometimes exhibit RF. It had been suggested that commonly in healthy adults, proactive task control is very efficient and hence the task conflict is not behaviorally evident under standard conditions, but can be observed in special conditions or with nonadults (e.g., Goldfarb & Henik, 2007; La Heij et al., 2010). In the following, we review studies that characterized this RF variability, with task contingencies and with individual differences.

Variability in Reverse Facilitation

Task Contingencies: Relaxed Control

In recent years, a variety of studies have revealed the conditions in which the Stroop RF, a behavioral indication for task conflict, arises. Goldfarb and Henik (2007) increased the Stroop neutral (i.e., *XXXX*) frequency to 75% and presented a cue, which indicated whether the upcoming trial was neutral or not, in 50% of the trials. This manipulation is thought to reduce or relax the proactive control level, as a result of the lower average conflict that the subjects experience in a block of trials (Botvinick et al., 2001; Tzelgov, Henik, & Berger, 1992) and due to the subjects' ability to deploy control at the cue (saving the effort of maintaining it throughout the block; Braver, Gray, & Burgess, 2007). Results yielded RF in the relaxed control condition ("Non-cued," Figure 2, left panel), but not when control is deployed in the cued condition. F2
More recently, RF was also obtained by increasing the frequency of nonletter strings neutrals (e.g., @#&*) to 80% even without cues that predict the presence of color-words (Entel, Tzelgov, Bereby-Meyer, & Shahar, 2015). These authors suggested that the nonletter neutrals activate the reading pathway to a lower degree than letter-strings do, revealing the presence of task conflict in response to a neutral frequency manipulation alone. Another similar manipulation that affects proactive control is the response-stimulus interval (RSI). Parris (2014) manipulated the RSI in a color-word Stroop task. Based on previous studies that suggested that short RSI enhances control levels (and long RSI relaxes control), Parris predicted that congruent and incongruent trial RTs would be shorter under the short RSI condition. Indeed, he found that although neutral trial RTs were not affected by the RSI

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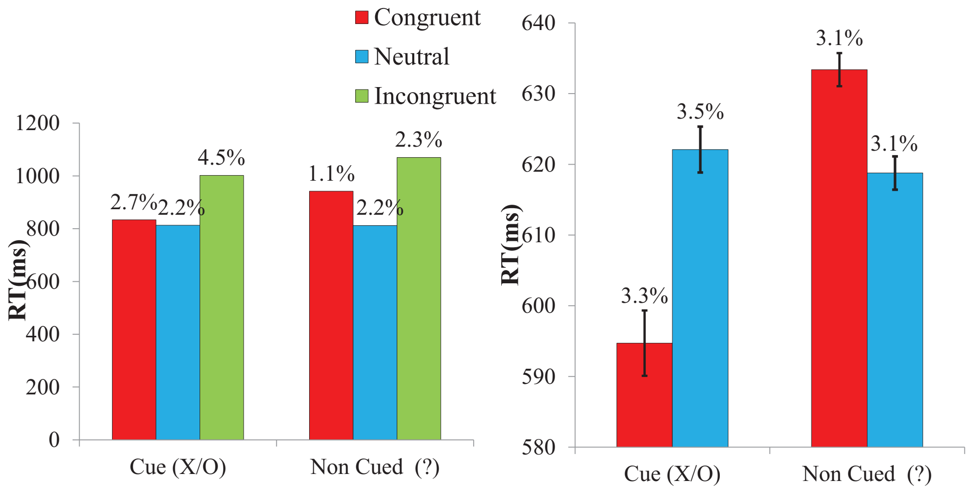

Figure 2. Left panel: Mean reaction time (RT) and error rates (above the bars) in the congruency conditions for Stroop trials with and without cueing in Experiment 1 of "Evidence for Task Conflict in the Stroop Effect," by L. Goldfarb and A. Henik, 2007, *Journal of Experimental Psychology: Human Perception and Performance, 78*, based on the data reported in Table 1. Copyright 2007 by American Psychological Association. Reprinted with permission. Right panel: mean RT and error rates (above the bars) in the congruency conditions for Stroop trials with and without cueing in Experiment 1 of "Stop interfering: Stroop task conflict independence from informational conflict and interference" by E. Kalanthroff, L. Goldfarb, M. Usher, and A. Henik, 2013, *The Quarterly Journal of Experimental Psychology, 66*, p. 1360. Copyright 2013 by The Experimental Psychology Society. Reprinted with permission of Taylor & Francis Ltd, www.tandfonline.com on behalf of The Experimental Psychology Society. Error bars represent 1 *SE* from the mean. Though the manipulation was similar in both studies, in the second experiment (right panel) there was no incongruent condition. See the online article for the color version of this figure.

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manipulation, both congruent and incongruent Stroop stimuli were faster under the short RSI and slower under the long RSI.

One question that these results raise is whether the slow-down in RT for words is an adaptive mechanism meant to protect the participant from potential errors (usually half of the color words are incongruent and likely to trigger mistakes) or whether it is automatic. To test this issue, Kalanthroff, Goldfarb, Usher, et al. (2013) replicated Goldfarb and Henik's (2007) results in a similar experiment, but without incongruent trials. These results (Figure 2, right panel) indicate that task conflict can occur even if participants face no threat for informational conflict. Notably, Bugg, McDaniel, Scullin, and Braver (2011) reported that although the interference effect was reduced in the high incongruent and high neutral proportion blocks, the facilitation effect was similar in all conditions. However, since in this study researchers used word-neutrals (thus all trials in this study contained real words), manipulating the proportion of incongruent or neutral trials affected only the information conflict (task conflict existed in 100% of the trials in all blocks) thus it cannot measure task-conflict.

Task Contingencies: Task-Switching and Control Overload

A different method to reduce the level of proactive task control is to require the participants to respond to both tasks (color naming and word reading) in different trials (Klein, 1964). This makes both of the tasks relevant to some degree, reflecting into a partial activation of both of the color naming and word-reading task demand representations (Cohen et al., 1990), and thus reduces the ability to activate proactive control in advance, making the task dependent on reactive control in conflict trials. This is the case, in particular, when the delay between the task cue and the Stroop stimulus is short. Using the task-switching paradigm, it has been shown that when proactive task control is undermined by constant switching between tasks, task conflict appears, as indicated by Stroop RF (Braverman & Meiran, 2010; Elchlepp, Rumball, & Lavric, 2013; Meiran & Daichman, 2005; Meiran & Kessler, 2008; Rogers & Monsell, 1995; Shahar & Meiran, 2015; Waszak et al., 2003). Specifically, some studies found RF when participants were asked to constantly switch between word reading and color naming in the Stroop task (Aarts et al., 2009; Kalanthroff & Henik, 2014; Steinhauser & Hübner, 2009). Kalanthroff and Henik (2013) found that when the interval between the task cue and the target (CTI) is short (i.e., less preparation time and therefore there is not enough time to activate the relevant proactive task control), one finds RF (Figure 3 left panel, 0 ms CTI condition); F3
at longer cue-stimulus intervals, a more common Stroop facilitation appears. Note that results also yielded a larger interference effect in the incongruent condition when preparation time was short.

A different manipulation that was found to generate consistent RF is control overload. Here participants are asked to carry out the Stroop task while they are also performing a concurrent high-load working memory updating task (*n*-back; de Fockert, Rees, Frith, & Lavie, 2001; Kalanthroff, Avnit, et al., 2015; Soutschek, Strobach, & Schubert, 2013). In a recent study, we found that a concurrent high load of working memory updating decreases the ability to maintain the proactive task control and thus generates RF (Figure 3, right panel; Kalanthroff, Avnit, et al., 2015).

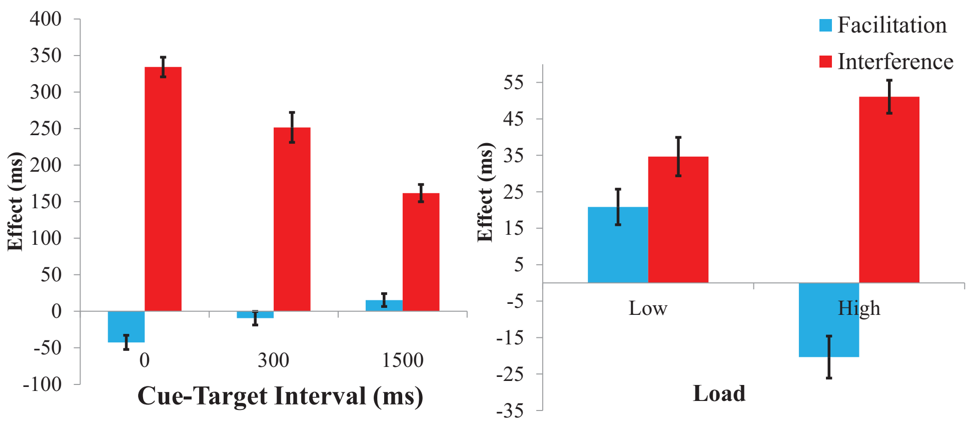

Figure 3. Facilitation (neutral minus congruent RT) and interference (incongruent minus neutral RT) in the (left panel) cue-target interval conditions for color-naming task in a Stroop task switching paradigm and (right panel) high and low concurrent working memory load conditions. RF corresponds to negative values. Error bars represent 1 SE from the mean. The left panel is from Experiment 1 of "Preparation Time Modulates Pro-Active Control and Enhances Task Conflict in Task Switching," by E. Kalanthroff and A. Henik, 2014, *Psychological Research, 78,* p. 281. Copyright 2014 by Springer-Verlag Berlin Heidelberg 2013. Reprinted with permission. The right panel is from "Stroop Proactive Control and Task Conflict Are Modulated by Concurrent Working Memory Load," by E. Kalanthroff, A. Avnit, A. Henik, E. J. Davelaar, and M. Usher, 2015, *Psychonomic Bulletin & Review, 22,* p. 872. Copyright 2015 by Psychonomic Society, Inc. 2014. Reprinted with permission. See the online article for the color version of this figure.

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Control Failure, Individual Differences, and Control Throughout the Life Span

Individual differences in proactive control are likely to appear as a result of the fact that proactive task control might fail from time to time, even for the same task conditions, depending on the efficiency of the control system. Using the stop-signal task, Kalanthroff, Goldfarb, and Henik (2013) 'zoomed in' on control failure trials in healthy student participants. This was done using a novel combined Stroop and stop-signal task (in which the go task was the Stroop task), which allowed the researchers to separately analyze the Stroop data on no stop-signal trials and on erroneous responses to stop-signal trials (i.e., when participants failed to inhibit responses although a stop-signal was given). The logic here is that the stop-signal provides an independent measure of the effectiveness of the control mechanism (Friedman & Miyake, 2004). As reported in this study (Kalanthroff, Goldfarb, & Henik, 2013), erroneous responses to stop signals (inhibition failure cases) showed an RF effect, while in no-stop-signal trials, a regular facilitation was found. This suggests that there is a connection between inhibitory control and Stroop proactive task control—a specific control failure caused both inhibitory failure in the stop-signal task and a larger indication of reduced control in the Stroop task. Building on these findings, Kalanthroff and Henik (2013) aimed to investigate the variability in proactive task control among individuals. This study showed that individual differences in inhibitory control (as measured by the stop-signal task) can predict individual differences in task conflict control (as measured by the RF: the RT difference in Stroop congruent and Stroop neutral trials). The participants were divided into six equal groups according to their stop-signal RT (SSRT; longer SSRT is associated with less efficient inhibitory control). As shown in Figure 4 (left panel), the results indicated that one sixth of the participants, with the longest SSRT, displayed a significant RF effect. Furthermore, significant (negative) correlations were found between SSRT and Stroop facilitation effect and between SSRT and the Stroop interference effect.

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With healthy adults, proactive task control is usually efficient and hence the task conflict is not behaviorally evident under standard conditions. With young children, on the other hand, task conflict is more evident due to their underdeveloped control processes (La Heij & Boelens, 2011). Ben-Shalom, Berger, and Henik (2013) asked young children, aged 5–6 years old, to complete the numerical version of the Stroop task and found a Stroop RF effect, without any additional manipulation (Figure 4, right panel). We further discuss task conflict in young children, in the context of a different conflict task, presented in the General Discussion.

Control deficits in the Stroop task, which are related to task-conflict, have also been reported in a number of pathologies, such as obsessive–compulsive disorder (OCD; e.g., Kalanthroff, Henik, Simpson, Todder, & Anholt, 2017), Schizophrenia (e.g., Barch, Carter, Hachten, Usher, & Cohen, 1999) and anxiety disorders (e.g., Kalanthroff, Henik, Derakshan, & Usher, 2016). Here we focus on the variability in control that results from task contingencies in normal populations, and we defer the discussion of patients' deficits in control to the General Discussion.

Variability in the Stroop RT-Distribution

Although a number of Stroop models can account for effects of mean-RT, these models are facing a challenge in accounting for properties of the RT-distribution of responses. For example, the Stroop model of Cohen et al. (1990), which accounts for an impressive amount of Stroop phenomena at the level of mean-RT, was criticized for failing to capture properties of RT-distributions (Mewhort et al., 1992). In particular, whereas in experimental data

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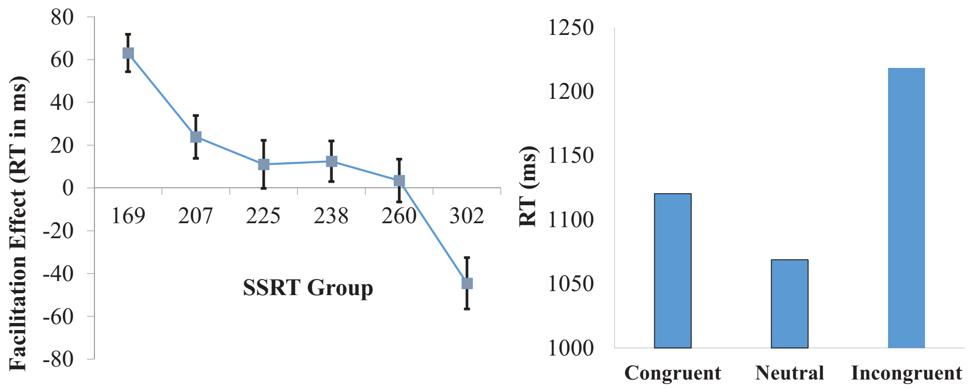

Figure 4. Left Panel: Facilitation effect (neutral minus congruent) in the different stop-signal RT (SSRT) groups (mean SSRT in milliseconds for each group appears on the *x*-axis). Note that for the 6th group (longest SSRT) facilitation reverses. Error bars represent one standard error from the mean. Right panel: RF in a numerical Stroop task with pre-school children. The left panel is from "Individual but Not Fragile: Individual Differences in Task Control Predict Stroop Facilitation," by E. Kalanthroff & A. Henik, 2013, *Consciousness and Cognition, 22,* p. 417. Copyright 2015 by Elsevier Inc. Reprinted with permission of Elsevier. The right panel is from "My Brain Knows Numbers! An ERP Study of Preschoolers' Numerical Knowledge," by T. Ben-Shalom and A. Henik, 2013, *Frontiers in Psychology, 4,* p. 716. Reprinted with permission of T Ben-Shalom and A. Henik (authors). See the online article for the color version of this figure.

the standard deviation (*SD*) of the RT distribution is larger for congruent trials than for neutral trials (see also, Kalanthroff et al., 2015; Kalanthroff, Goldfarb, & Henik, 2013; Kalanthroff & Henik, 2014), the model produced simulated response times that showed a reversed pattern (larger RT-variance in neutral than in congruent trials). This was true across a wide range of parameter values. Based on their simulation results, Mewhort et al. concluded that the Cohen et al. model accounts for mean response time for the wrong reason and that therefore it is not adequate to account for the actual behavior. To our knowledge, none of the further developments of the Cohen et al. model have been applied to the issue of the reversed *SD* pattern. Including task-conflict within the Stroop model, however, offers an opportunity to account for this challenge. As both congruent and incongruent (but not neutral) trials trigger task-conflict, the dynamics underlying the conflict resolution allow the extended model to offer an answer to the variability challenge.

To summarize, we reviewed studies demonstrating that variability in Stroop RF arises in response to task contingencies within the same individual, or across individuals in the same task. The interpretation we propose is that this variation is due to systematic changes in the proactive task control that the participants can recruit. This control process can vary as a result of task contingencies, such as the time from task cue to stimulus, cognitive load, or the effectiveness of the control system. We suggest that when this happens, the participant experiences not only informational, but also task conflict and we will argue that these two types of conflict (as measured by RF and by the total Stroop effect) can dissociate. Taking this as our working hypothesis, we set out to provide a computational theory that explains how conflict is resolved and how these two types of conflict processes interact, accounting for the dependency of Stroop facilitation (reverse or standard) on experimental conditions, as well as for the variability of RT-distribution challenge (Mewhort et al., 1992). We formulate this theory in the next section.

A Computational Stroop Model of Reverse Facilitation

A number of prominent computational models of the Stroop task have been proposed (Botvinick et al., 2001; Cohen et al., 1990; Melara & Algom, 2003; Wyble, Sharma, & Bowman, 2008). However, previous Stroop models did not account for the effects of task conflict, hence did not predict the Stroop reverse facilitation (RF). Here, we present a computationally explicit model of conflict resolution that accounts for the RF variability, as well as standard Stroop data, and which explains the mechanism of conflict resolution and the interaction between the informational and task conflict. The model extends the control model of Cohen, Botvinick and colleagues (Botvinick et al., 2001; Cohen & Huston, 1994) and it shares some similarity with a previous DMC Stroop model, which was applied to behavioral and imaging data from a Stroop study that varied the amount of informational conflict (percentage of incongruent or neutral trials) between Stroop blocks (De Pisapia & Braver, 2006), but it also differs from it in some important aspects. To distinguish our model from previous DMC implementations, we refer to it as the proactive control/task conflict (PC-TC) model.[1] A brief presentation of the model was recently presented in Kalanthroff et al. (2015), showing an account of concurrent working memory load in the Stroop task. Here, this model is presented in more detail and extended to additional task conflict data and to account for properties of RT distributions. Fn1

[1] We see our model as an extension of the Botvinick et al., control model with the inclusion of task-conflict resolution. These models follow the GRAIN (graded, random, interactive networks; McClelland, 1993) framework, in which feed forward inhibition is replaced with lateral inhibition and connections are bidirectional (involving feedback). Here, we implemented the bidirectionality in the connections between the feature layers and the task-demand layer, but not in the connection between the feature units and the response layer (as this could create "perceptual illusions").

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PC-TC Model Assumptions

The model is a simple connectionist model (see Figure 5), in which two parallel sources of stimulus–response associations provide information from color and lexical representations to a common set of response representations. All units have sigmoidal activation functions and the automaticity of the lexical pathways is reflected in stronger weights (thick lines in Figure 5) for the lexical, compared with the color pathways. In this model, control is modeled via a set of task-demand representations (color naming vs. word reading), associated with the prefrontal cortex (Cohen & Servan-Schreiber, 1992), which project input top–down to their input representations to help them overcome the response competition from the task-irrelevant representations (Botvinick et al., 2001; Cohen et al., 1990; Wyble et al., 2008). Finally, the task-demand units themselves are top–down modulated by a regulatory process, which depends on previous trial history and on block modulations (Botvinick et al., 2001; Cohen & Huston, 1994), via a variable parameter of proactive control (PC), which as in Botvinick et al. (2001) we assume to originate from the ACC. All connections between layers are excitatory, and all the connections between units in a single layer are inhibitory, corresponding to the competitive interactions (Botvinick et al., 2001; McClelland, 1993; Usher & McClelland, 2001).

One important characteristic of the model is that the connectivity between the color and lexical input layers and their respective task demand is bidirectional (see also Botvinick et al., 2001). This implies that not only does the task demand activate the input representations top–down, but conversely, the input units activate the task representations bottom–up. The latter process takes place when the proactive control is weak,

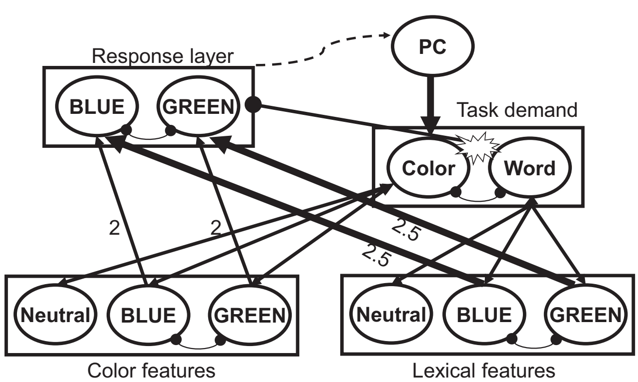

Figure 5. Architecture of the proactive task control (PC-TC) model of the Stroop task. Pointy-headed arrows represent excitatory connections, whereas the round-headed arrows represent inhibitory connections. A stimulus activates its color and lexical representations in the input (features) layers. The activations from the input layers propagate to the response layer and to the task demand layer, which feeds back to the input layers. Color words, but not (nonword) neutral stimuli activate both task demand units, which lead to task conflict. This task conflict inhibits the response layer and thereby slowing down responses to color words and thus creating a reverse facilitation effect. When proactive control is high, there is enough top–down bias to the color-naming task demand unit to prevent task conflict and allow for a net Stroop facilitation effect. Task manipulations that affect the amount of proactive control will in turn affect the balance between positive and reverse facilitation.

and leads to task conflict—both task-demand units become active. On the contrary, when proactive control is strong, the effect of the bottom–up activation of task units is negligible due to the top–down PC input that resolves rapidly the competition between the two task demand units and prevents the activation. Thus, the presence of task conflict in our model, which is implemented as a conflict between the two units of the task-demand module, is predicated by a weak proactive control process. All types of conflict (informational or task) are computed via the multiplication of the activations of the corresponding competing units (Botvinick et al., 2001). Thus, informational conflict is the multiplication of the competing response unit activations (blue/green lines in Figure 6, second column), and the task conflict is the multiplication of the color/word task-demand unit activations (black/cyan lines in Figure 6, first column). Conflict is thus maximal when both response (or task) units are active.

A central assumption of our model is that the task conflict inhibits *all* response representations, corresponding to the intuitive notion that when there is uncertainty about what task needs to be done, we put a brake on the response (see also Davelaar, 2009; Frank, 2006). This is similar to raising the response threshold. We do not assume that there is a direct inhibitory pathway from conflict to response units. Instead, a conflict-dependent change of response threshold is consistent with a neural mechanism, according to which conflict monitored at preexecution stages (prior to the activation of the striatum) activates the subthalamic nucleus, which in turn activates the globus pallidus, and thus leads to inhibition of the thalamus (e.g., see Frank, 2006). This cortico-basal-thalamic pathway is known as the hyperdirect pathway (Nambu, Tokuno, & Takada, 2002) and activating it is functionally equivalent to a direct inhibition between task conflict and response representations. The task conflict response inhibition mechanism may also be adaptive (see Bogacz & Gurney, 2007; Davelaar, 2009), protecting us from making errors (in the case of incongruent trials), but might also have an automatic component (Kalanthroff, Goldfarb, Usher, et al., 2013). Thus, task conflict, which appears in both congruent and incongruent Stroop trials under conditions of low proactive control, slows down the RT.

The mechanism for resolving task conflict differs from the one that was proposed in a previous implementation of the DMC model (De Pisapia & Braver, 2006). Whereas the latter model assumed two independent task-demand representations, one for proactive and the other for reactive control, with the latter activated by the online (within trial) detection of informational conflict, in our model (as in the original Botvinick at al model), a single set of task-demand representations are assumed. To implement reactive control, we assume that this is dependent on the amount of (proactive control) activation that projects from the slow ACC conflict module (Botvinick et al., 2001). When this activation is high, no task conflict arises. When it is low, reactive control comes into play to resolve task conflict via the weak top–down input from this ACC module that biases the competition between the task demands in favor of the task-relevant one (Figure 6, left column, congruent and incongruent). This allows us to make task conflict resolution not contingent on informational conflict within the same trial (De Pisapia & Braver, 2006), and thus to account for Stroop RF. We illustrate the operation of the model in the next section.

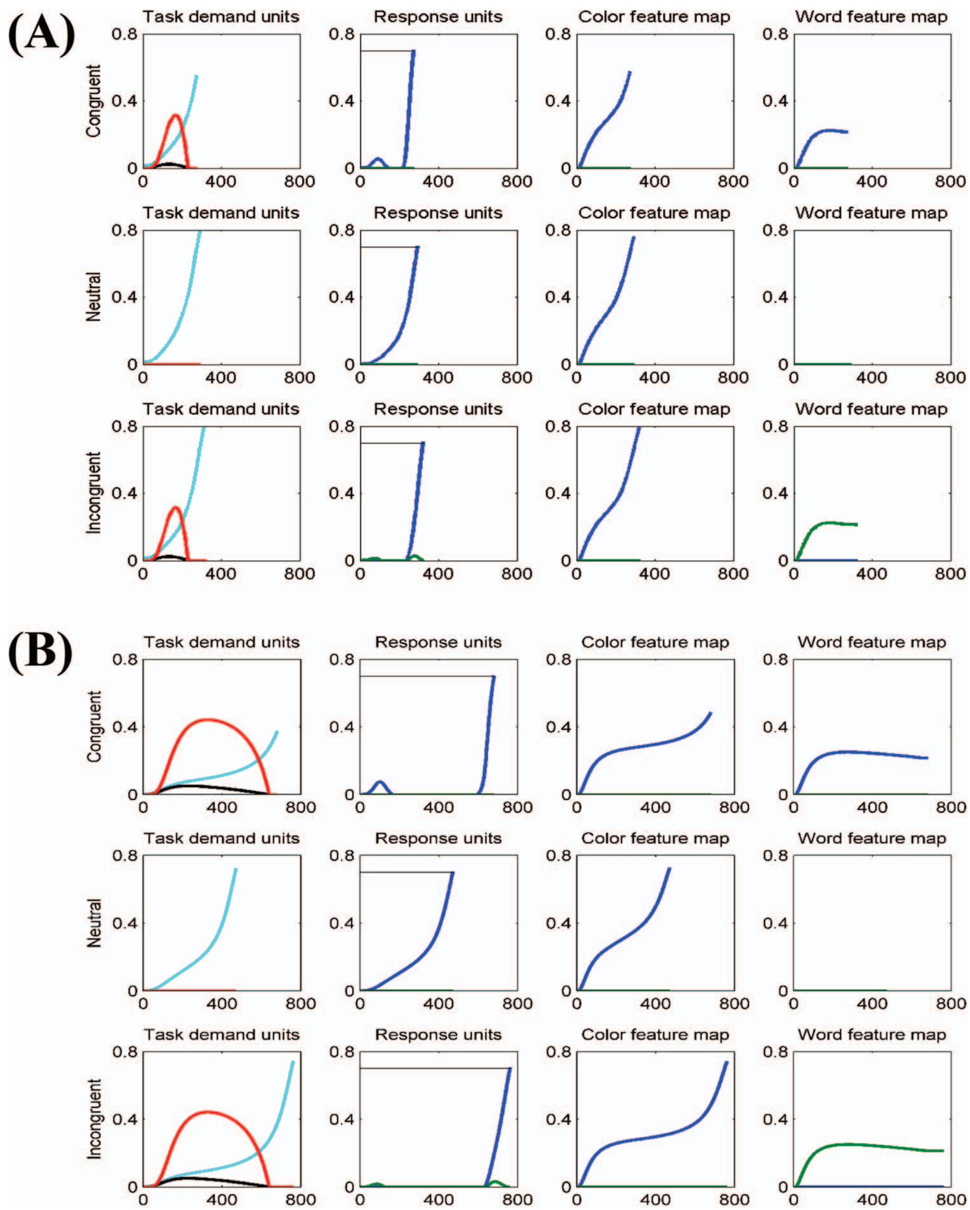

Figure 6. Activation trajectories. The model simulates the three Stroop conditions in situations of high proactive control (Panel A; PC = 0.15) and low proactive control (Panel B; PC = 0.025). The top, middle, and bottom rows relate to congruent (*BLUE* in blue), neutral (*XXXX* in blue), and incongruent (*GREEN* in blue) trials, respectively. Columns 3 and 4 show the activation levels in the color and word features layers, respectively. The line colors correspond to the color indicated by the stimulus in that particular trial. Column 2 shows the activations of the response units, with the blue and green activations corresponding to the correct and incorrect response respectively. The black horizontal line corresponds to the response threshold. Finally, the first column shows the activations of the task demand units (color-naming and word-reading are cyan and black colored, respectively). The amount of task-conflict over time is represented by the red activation lines in the panels of the first column. See the online article for the color version of this figure.

The model was simulated for congruent, neutral and incongruent trials with high and low proactive control. Low proactive control can be due to either task contingencies, such as a reduced vigilance and effort in response to a high frequency of neutral Stroop trials, task-switching, or working memory load, or due to individual difference characteristics. To illustrate the model behavior, we first show paradigmatic activation trajectories (without noise) to high/low proactive control levels, illustrating the change from normal to reverse facilitation. We then demonstrate that the model can fit RT data from Stroop experiments and we then consider the effects of noise, to explain predictions about variability in RT within a single Stroop trial and condition.

Qualitative Model Behavior and Reverse Facilitation

We present here an illustration of the activation trajectories of the various model units in response to congruent, incongruent and neutral Stroop stimuli. As the model is quite complex, we ran these simulations without noise to investigate the dynamics of the model that leads to Stroop RF effect. This is justified by the low error rate in the Stroop data we address and is consistent with most previous Stroop models (Botvinick et al., 2001; Cohen et al., 1990; De Pisapia & Braver, 2006; Wyble et al., 2008). However, we will examine the impact of noise on the distributions of the response latencies in Section 4.

Simulation methods. All units are initialized to zero at the beginning of the simulation. Each simulation run starts with a settling period of 500 time steps, after which the input units representing a Stroop stimulus are set to 1 for the remaining duration of the trial (congruent = [1, 0, 1, 0]; incongruent = [1, 0, 0, 1], neutral = [1, 0, 0, 0]). During the settling period, the proactive control unit sends input to the color-task-demand unit. The activations of all units are updated on each time step until one of the response units reaches the threshold (set at 0.7). The time from turning on the input up to the crossing of the threshold is the simulated response time. All units x_i are updated in parallel as follows:

$$x_i(t+1) = \lambda * x_i(t) + (1-\lambda)\{\text{netinput}_i - \beta * \textstyle\sum_{j \neq i} F[x_j(t)]\},$$

where t is the iteration time step and $\lambda = 0.97$ is the integration constant. Each unit i in a layer competes with unit j in the same layer with β (= 1.9 for the task-demand units, 1.3 elsewhere) governing the mutual inhibition. The *netinput* to a unit is the sum of the weighted output activations sent from other layers, supplemented by layer-specific inputs. For the input layers, the netinput includes the external input (1 or 0, depending on the congruency condition) minus a bias (set to 0.3) to prevent surreptitious responding, due to the input units receiving top–down input that can trigger the positive feedback loop into driving the response units. For the response layer, the weighted input is supplemented by the inhibition from task conflict. For the color-task-demand unit, the weighted input is supplemented by the sustained bias, PC, from the proactive control unit. The output activation function $F(x)$ is a sigmoidal neural activation function that imposes firing rate saturation at high activation rates and is constrained to be zero when no internal activation is present: $F(x) = 1/\{1 + \exp[4*(1-x)]\} - c$, with $c = 1/(1 + \exp(4)) = 0.0179$. All model parameters are presented in Table 1. T1 The task conflict, H is updated at every timestep, in the same way as Botvinick et al. computes response conflict: $H = \beta_{task} \times F(x_c) \times F(x_w)$. Where β_{task} is the inhibition between the task demand units and $F(x_c)$ and $F(x_w)$ are the activation levels for the color-naming unit and word-reading unit, respectively.

Simulation results: Single trial illustration. In Figure 6, we show the activation trajectories of the model units in response to congruent (*BLUE* written in blue color), incongruent (*GREEN*, written in blue), and neutral (*XXXX* written in blue) Stroop stimuli (in each figure, blue/green colors correspond to blue/green units). We observe that the color-task-demand unit (cyan, in column 1) shows an increase in all trials, as the activation in the color feature map activates this task unit. As the task unit provides top–down input to the color feature maps, an accelerated activation due to positive feedback can be seen in both layers. As a result of the top–down bias from the ACC and the inhibition between the color- and word-task-demand units, we see that the color-task-demand unit wins the competition with the word-reading-task unit (black, in column 1), even when the PC parameter is low (panel B), but this takes longer, generating task conflict (red, in column 1) and delaying the RT.

To understand the model dynamics that gives rise to RF, consider first the situation with high proactive control (panel A, PC value = 0.15). For the neutral condition (middle row), the model activates the blue color feature unit, which in turn sends bottom–up activation to the color-task-demand unit. The task-demand unit and the color feature lock into a positive feedback loop. During this period, the response unit (blue) increases in activation and reaches the response threshold. As the word-task-demand unit does not receive input, no competition or task conflict is observed. In the congruent and incongruent conditions, however, task conflict does occur (red in column 1), because both task-demand units receive input from the feature maps. However, due to the high level of proactive control, the competition is resolved quickly and task conflict does not lead to RF, as the delay caused by task conflict is smaller than the facilitation due to convergent input in congruent trials. The slower response time for incongruent

Table 1
Model Parameters With Description and Values

Parameter	Description	Value
Control_To_Color	Control → color layer	1
Control_To_Word	Control → word layer	1
Color_To_Control	Color → control layer	2
Word_To_Control	Word → control layer	2
Color_To_Response	Color → response layer	2
Word_To_Response	Word → response layer	2.5
Task_Conflict_To_Response	Task conflict → response layer	500
Response_Threshold	Response threshold	0.7
Inh	Within-layer inhibition for color, word, and response layers	1.3
Inh_t	inhibition between task control units	1.9
Bias	Bias to word and color layers	−0.3
Λ	Euler integration constant	0.97
PC	Proactive control	Low =0 .025, high = 0.15
Settle_Time	Interval before stimulus presentation	500 time steps

trials is due to the informational conflict that exists only for the incongruent conditions. The corresponding response times in simulation time steps are $RT_{congruent} = 274$, $RT_{neutral} = 294$, and $RT_{incongruent} = 322$. The maximum amount of inhibition sent to the response units from task conflict is 1.57.

Consider now the situation with low proactive control (panel B, PC value = 0.025). For the neutral condition, nothing changes much. The lower proactive control bias only leads to a slower ignition of the positive feedback loop between the color-task-demand unit and the color-feature unit. Again, both the congruent and incongruent conditions contain task conflict (red, in column 1). With low levels of proactive control bias, the word-task-demand unit (black) becomes activated and competes with the color-task-demand unit (cyan). The resulting task conflict (red) inhibits the response layer, effectively blocking any response (both correct and incorrect) from being made. Only when the competition in the task-demand layer is resolved, as shown by a decrease in task conflict, is the model able to emit a response. This means that with lower levels of proactive control, the task conflict can reach such high levels that it halts the responses to congruent stimuli and slows it down beyond that of the response time for neutral stimuli. The corresponding response times in simulation time steps are $RT_{congruent} = 681$, $RT_{neutral} = 472$, and $RT_{incongruent} = 762$. The maximum amount of inhibition sent to the response units due to task conflict is 2.21.

Simulation results: 2. Dissociations between measures of task and information conflict. Using the model, we can demonstrate that, although both task and information conflict are contingent on proactive control, there are nevertheless conditions that dissociate between measures that are traditionally associated with information-conflict (such as the total Stroop effect, and the Stroop interference) and measures that are associated with task-conflict (RF). In Figure 7, we show how these three measures (i.e., facilitation, interference, and Stroop effects) depend on the level of PC, under two model regimes: (a) the intact model with task-conflict to response inhibition in place (red lines), and (b) a model in which this inhibitory link is lacking (blue lines; as we propose to be the case for patients with schizophrenia; see General Discussion).

Two important patterns stand out in this model. First, the task-conflict to response inhibition link (i.e., the inhibitory link between task conflict and the response units; see Figure 5) has a major effect on the Stroop facilitation score (Figure 7 left panel), but not on the Stroop interference (middle panel). Second, we see that the impact that small changes of PC (open vs. filled circles, Figure 7 right panel), which can take place as a result of trial by trial control adjustments (Botvinick et al., 2001), has on the Stroop effect (in the intact model; red line, Figure 7 right panel) is contingent on the baseline PC-value, instantiating another dissociation between the facilitation and the total Stroop score. For example, a small decrease in PC at relatively low PC-baselines (from open to filled red circles, in Figure 7 right panel) results in an increase in the Stroop effect, whereas a similar change at higher PC-baselines (from open to filled black circles, in right panel) has no effect on the Stroop effect (in the General Discussion we show that under different model parameters the model can predict that a decrease in PC decreases the Stroop effect). Under both baselines (solid red/black circles), however, the effect of Stroop facilitation is similar: The facilitation scores increase with proactive control.

To summarize, the model accounts for a shift from positive to reverse facilitation with the degree of proactive task control, which is not always associated with a parallel change in the total Stroop effect. We now turn to applying this model to quantitatively account for specific Stroop data.

Quantitative Data Fitting: Task Contingencies

In the introduction, we reviewed recent work suggesting that proactive control is weaker when: (a) a cue presented before a Stroop stimulus is uninformative (e.g., Goldfarb & Henik, 2007), (b) the time available to process the cue is very short (e.g., Kalanthroff & Henik, 2014), and (c) concurrent working memory is processing a high cognitive load (e.g., Kalanthroff, Avnit, et al., 2015). An additional data set that involves effects of emotional distractors on Stroop proactive control in participants that are suffering from anxiety (Kalanthroff et al., 2016), presented in the General Discussion, is also examined. To test the feasibility of this proposal, we fitted the model to these four experimental manipulations with the constraint that only the value of the PC was allowed to vary across conditions, while

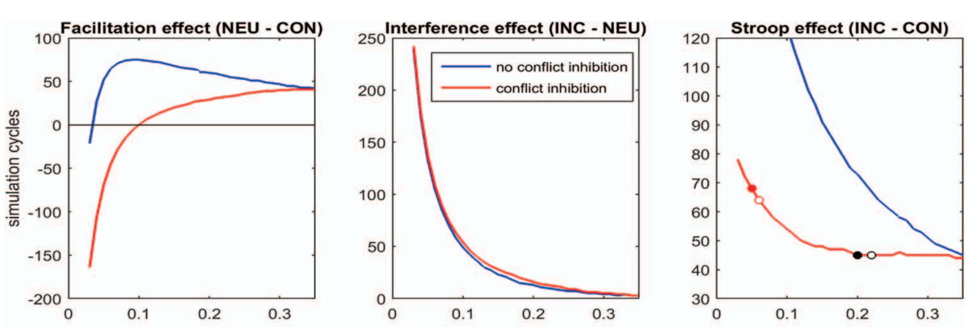

Figure 7. Model simulations of Stroop measures as function of proactive control and the presence of task-conflict to response inhibition. Left: Stroop facilitation effect, calculated as $RT_{neutral}$ minus $RT_{congruent}$. Middle: Stroop interference effect, calculated as $RT_{incongruen}$t minus $RT_{neutral}$. Right: Stroop effect, calculated as $RT_{incongruent}$ minus $RT_{congruent}$. The open and filled circles in the right panel show an example in which the effect of changing proactive control depends on the baseline level (filled circle) of proactive control. These functions were created using the nonstochastic model with the default parameters in Table 1. See the online article for the color version of this figure.

other parameters were kept constant. This not only puts all the weight on the PC parameter, it also allows a direct qualitative test to see if all conditions under which RF is obtained have indeed lower PC parameter values compared with the normal facilitation conditions.

Method. The model was quantitatively fitted to each of the four data sets. For each dataset, a single model parameter—the inhibition between task-demand units—was free to vary. The predicted number of time steps produced by the model was converted to response times through linear regression for which the slopes and intercepts were free to vary across data sets (fitted simultaneously). The fitting procedure minimized the sum of squared deviation using the simplex method by changing the parameters for proactive control, task demand inhibition, slope, and intercept. Each dataset was fitted separately with at least 10 different starting values of these parameters using the model without noise.

Results. The results are shown in Figure 8. As shown in each panel, the model is able to quantitatively capture the observed empirical data by varying only a single model-parameter across the proactive control conditions (high vs. low as manipulated in the different experiments). This lends formal support for the view that the RF in these data sets is due to a single process, which we put forward as the change in proactive control that counters task conflict, slowing down the response to color words. Note that although our main focus is on the RT difference between Stroop neutral and Stroop congruent trials, the proactive control also influences the Stroop incongruent trials. This is most clear in Figure 8 (top left) where the interference effect ($RT_{incongruent}$ − $RT_{neutral}$) is shown. The full set of fitted parameters is presented in Table 2. The model is consistent in the qualitative ordering of the PC values and across the data sets the values for low and high PC conditions are clearly separated. F8 T2, AQ: 3

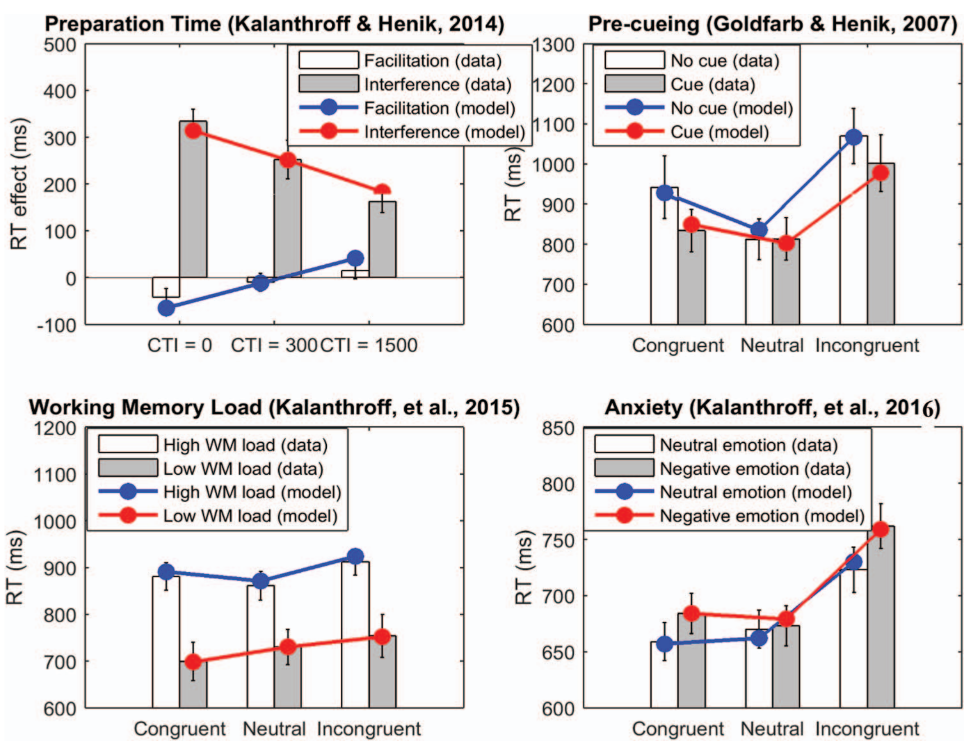

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Figure 8. Top left: Model fit to the data of Kalanthroff and Henik (2013), Experiment 1) in which the cue–target interval (CTI) was varied. With a larger CTI, more time is available to prepare the system for controlled processing on the Stroop stimulus (i.e., tuning PC levels) and thus a modest positive Stroop facilitation can be found. Top right: Model fits to the data of Goldfarb and Henik (2007, Experiment 1) in which a high frequency of neutral trials is assumed to lower the level of proactive control. On 50% of the trials a cue warns the participant that the upcoming stimulus is a neutral stimulus or a color word, which triggers control for that stimulus. The noncued trials reveal the full effect of having lower levels of proactive control, as shown by the reverse facilitation. Bottom left: Model fit to the data of Kalanthroff, Avnit, Henik, Davelaar, and Usher (2015), in which participants responded to Stroop stimuli while simultaneously being engaged in either a 0-back (low load) or a 2-back (high load) task. The increased load on working memory resources is assumed to impede the participant's ability to exert proactive control, leading to the appearance of reverse facilitation. Bottom right: Model fit for Kalanthroff, Henik, Derakshan, and Usher (2016), in which irrelevant neutral and negative affective cues were briefly introduced prior to each Stroop trial (Task data from "Anxiety, Emotional Distraction, and Attentional Control in the Stroop Task" by E. Kalanthroff, A. Henik, N. Derakshan, & M. Usher, 2016, *Emotion, 16*, p. 298. Copyright 2015 by American Psychological Association). Reprinted with permission. See the online article for the color version of this figure.

Table 2
Model Parameters for the Four Studies Manipulating Proactive Control

Study/Conditions	Proactive control	Task demand inhibition	Slope (ms/cycle)	Intercept (ms)	R^2
Kalanthroff & Henik (2014, Exp. 1)					
CTI = 0 ms	.031	3.03	2.05		.983
CTI = 300 ms	.039				
CTI = 1,500 ms	.052				
Goldfarb & Henik (2007, Exp. 1)					
No cue	.043	2.24	1.58	159	.978
Cue	.054				
Kalanthroff et al. (2015)					
High WM load	.15	1.41	1.82	327	>.999
Low WM load	.28				
Kalanthroff et al. (2016)					
Negative emotion	.096	1.89	1.39	198	.981
Neutral emotion	.107				

Note. All other parameters are as in Table 1, except for task demand inhibition between the two task demand units, which varies across experiments. CTI = cue–target interval between the task cue and the target; WM = working memory.

Model Predictions of Sequential Effects in the Stroop Task: The Gratton Effect

The main focus of the current paper is to account for Stroop variability as a result of block-wise experimental manipulations and of individual differences. However, the model can also account for trial-level sequential effects on Stroop RT. To do this all we need is to import the sequential conflict-control updating mechanism from the Botvinick et al. (2001), model. Consistent with this, we can assume that after an incongruent Stroop trial, PC is slightly stronger (say by 10%; Botvinick et al., 2001) than after a congruent or neutral Stroop trial. Figure 7 (right panel) shows that the model predicts a reduction of the total Stroop effect (going from the filled to the open circles) and a Gratton effect—a modulation of the Stroop effect, as a function of congruent/incongruent stimuli in the previous trial (Gratton, Coles, & Donchin, 1992)—at relatively low PC baselines (red circles), but not at higher PC-baselines (black circles). We defer the discussion of such contingencies to the General Discussion.

Beyond Mean-RT: Introducing Noise in Neural Trajectories

As our model extends the framework of the connectionist model of Stroop (Cohen et al., 1990; Cohen & Huston, 1994; Wyble et al., 2008) to task-conflict resolution, it is possible that it inherits the same problems that Mewhort and colleagues identified for the Cohen et al. (1990) model. Although a quantitative account of RT distributions and accuracy across a range of manipulation using our model is beyond the scope of this paper (the model is complex and nonlinear, and thus requires a dedicated investigation), we wish to demonstrate that its qualitative predictions are consistent with the RT-variability data, and thus are not subject to the criticism raised by Mewhort et al. As we show here, our model predicts that the larger standard deviation for congruent compared with neutral trials is due to stochastic noise at the task-demand level. The inability of the Cohen et al. model to account for the reversed *SD* pattern in RT-distribution in the Stroop task indicates that the distributions may be influenced by additional processes on top of those that occur inside the stimulus-response channel. One possible process is the resolution of the task conflict. During the process of accounting for the Stroop RF effect, we noticed that our model did not exhibit the problem observed by Mewhort et al. We explored the model under a range of different noise-parameter settings. We present here the results for a moderate amount of task noise and then demonstrate the model's ability to provide good quantitative fits to mean RT, while showing a good qualitative prediction of the reversed *SD* pattern.

Stochastic Simulation 1: Illustration of Two Noise Components

Method. We use the model described (see Figure 5) with the standard parameters (see Table 1) and we applied Gaussian noise at either the response ($\sigma_{response} = 1$) or the proactive task control ($\sigma_{task} = 0.1$) units. To illustrate the effects of noise at the two levels, we plot the RT distributions that result under both high and low PC, for the three types of Stroop trials, for each noise type, separately. Finally, we report the ranking of the model predictions for the *SD* of the RT distributions for the three conditions.

Results. Table 3 shows the average of the means and standard deviations of 10 RT distributions for each of three levels of proactive control (0.05, 0.10, and 0.15) and the two types of noise, for congruent and neutral trials; the lower rows give the difference in mean RT and *SD* between the conditions. T3

The results in Table 3 show that with increase in proactive control, the facilitation effect ($RT_{neutral} - RT_{congruent}$) goes from negative to positive in both noise-added scenarios. In addition, the standard deviations of the RT distributions are larger for neutral than for congruent Stroop stimuli when noise is added to the response units only. This replicates the analyses by Mewhort et al. (1992). However, when noise is added only to the task-demand units, the pattern reverses, with the standard deviations of the RT distributions of congruent stimuli becoming larger than those of neutral trials (a difference that shrinks as PC increases) as reported in empirical studies.

The top row in Figure 9 shows the predicted response time distributions from our model (using 10,000 trials) when zero- F9

Table 3
Simulated Mean RTs and Standard Deviations of RT Distributions

PC level	Response-layer noise *M*	Response-layer noise *SD*	Task-demand noise *M*	Task-demand noise *SD*
		Congruent		
.05	483	11	486	28
.10	340	9	341	12
.15	273	9	274	8
		Neutral		
.05	408	19	415	11
.10	336	16	341	7
.15	290	14	294	5
		Neutral—Congruent		
.05	−75	8	−71	−17
.10	−4	7	0	−5
.15	17	5	20	−3

Note. Simulated mean reaction times (RTs) and standard deviations of RT distributions with noise added to the response layer (response-only noise) or the task-demand layer (task-only noise) under different levels of proactive control for congruent and neutral Stroop trials (each value is the average of 10 × 1,000 simulated trials). Other parameters are as in Table 1. PC = proactive control.

mean Gaussian noise is added only to the response units, for conditions of low and high proactive control (PC = 0.05 and PC = 0.15, respectively). The vertical lines indicate the predicted response times when no noise is added. For both panels in the first row, the ranking of the standard deviations is CON < INC < NEU. The bottom row of Figure 9 shows the predicted response time distributions from our model when noise is added to the task-demand units. The distributions are markedly different. The ranking of the standard deviations is NEU < INC ~ CON. Note that the rankings of the standard deviations are independent of the RF effect (they take place for both high and low proactive control).

The specific effect of noise on task-demand units on RT-variability can be explained as follows. Noise on these units makes the process of task conflict generation more variable across trials. This variability involves the time at which the conflict is generated or its presence. As the task conflict is only triggered by color word stimuli, the noise will greatly affect the RT-variability in the trials with color words (congruent/incongruent Stroop stimuli) but not in nonword neutral trials. Thus, the standard deviations of the color words (congruent or incongruent) are increased by control noise, causing the ranking of the standard deviations to be NEU < CON, as shown in actual data. The RT distributions of incongruent trials have larger standard deviations than the distribution of congruent trials when informational noise is present, suggesting that the full empirical ranking of NEU < CON < INC is due to noise at both the informational *and* proactive task control levels.

Stochastic Simulation 2: Fits to Mean-RT Data and Predictions for RT-Variability

The distributions in Figure 9 are very narrow due to the small amount of noise added to allow the independent effects of both noise sources to be discerned. To truly test the model's ability to capture the reversed *SD* pattern as well as the RF as a function of PC, we used the stochastic model with both noise sources and fit it (via its noise parameters) to the WM load data of Kalanthroff et al. (2015). In particular, the model was only fitted to the mean-RT, and not to the *SD* of RT, which constitutes a model prediction.

Method. We kept the model parameters as in the deterministic model from Table 2 that best-fitted the mean RTs in the WM data (see Figure 8): $PC_{high\ load} = 0.15$, $PC_{low\ load} = 0.28$, and task-demand inhibition (between the two task demand units—word & color) = 1.41 and we only fitted the two new noise parameters. We imposed constraints on the noise values such that the accuracy for all six conditions was larger than 95% (as was in the data), while having enough variability in the RT distributions. The model was run for 1000 runs per condition per combination of a wide range of noise values. The model with the noise combinations that produced the best fit to the data ($\sigma_{response} = 0.5$, $\sigma_{task} = 1$, slope = 1.58, intercept = 374) was then used to make predictions for the standard deviations in each condition. We allowed for a constant intercept, in the mapping of *SD* of model RT to the data, which corresponds to variability in the nondecision component (see Ratcliff, Smith, Brown, & McKoon, 2016).

Results. Accuracy in all conditions were at ceiling, except in the incongruent under low PC condition (98.4%).[2] Figure 10 shows the simulated RT-distributions for the three congruency conditions in both WM-load conditions. Given that the model was not developed with RT distributions in mind, the profiles are quite remarkable. The model exhibits the RF effect as before, indicating that the addition of two sources of noise to a deterministic model fitted to mean RT does not undo to the RF effect with noise. Fn2, F10

In Figure 11, we show that the model can reasonably fit the experimental data from the WM-load experiment (Kalanthroff, Avnit, et al., 2015), focusing on mean-RT and on *SD* of the RT. In the left panel of Figure 11, the data and model fits are shown. In the right panel in Figure 11 are the mean SDs for each of the conditions in the data together with the model predictions. The resemblance is striking and shows that the model can account for effects in mean RT and *SD*, simultaneously. F11

Discussion: Introducing Noise in Neural Trajectories

The stochastic versions of the model demonstrate that the qualitative predictions of the deterministic model are maintained when noise is included, so as to account for within-subject RT-variability. The simulations also show that the model accounts for the effects of reduced PC on mean-RT, while predicting a particular effect for RT-variability, which helps to resolve a criticism raised against previous variants on the Stroop model: larger variability in congruent compared with neutral conditions (Mewhort et al., 1992). This results from the fact that task conflict interacts with noise on task demand units, generating a larger variability in the congruent compared with the neutral condition.

[2] In the data, there was a 3% error rate in all conditions (Kalanthroff, Avnit, et al., 2015), which we assume to reflect motor or response deadline errors. We thus assumed that (subject to such processes) the participants are at ceiling in their task performance However, if we decrease the response-criterion (from .7 to .5), this results in a reduction of the accuracy to .96 in the incongruent condition with similar results for the facilitation and interference scores (see Suppl. Materials).

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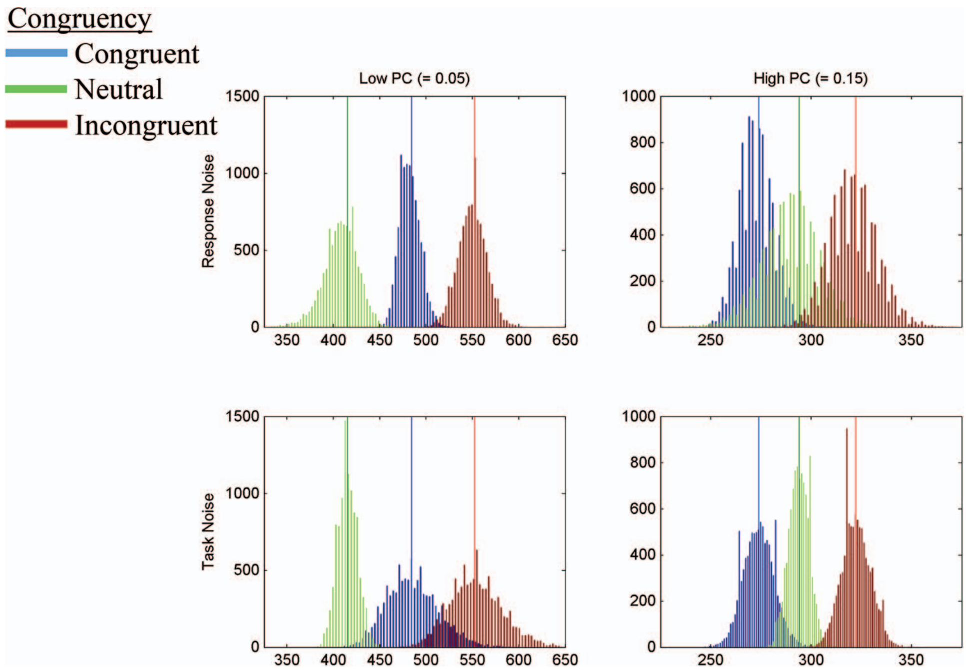

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Figure 9. Model predictions for response time distributions when zero-mean Gaussian noise is added either to the response units (top two panels) or to the task-demand units (bottom two panels) under conditions of low proactive control (left two panels) and high proactive control (right two panels). Distributions are based on 10,000 trials. Shown are congruent (blue; light gray), neutral (green; gray), and incongruent (red; dark gray) conditions. Note that with low PC reverse facilitation is obtained, irrespective of which layer receives noise. Note also that the neutral distributions (green; gray) are wider than the congruent distributions (blue; light gray) in the top panels, with the reversed situation when noise is added to the task-demand layer only (bottom panels). See the online article for the color version of this figure.

The simulations (Figure 10 and 11) also highlight two important points of the PC-TC model. First, the addition of noise in and of itself either at the level of the response units or at the level of task units cannot produce the reverse facilitation effect seen in the studies reviewed in the introduction. It requires a process that is outside the stimulus-response channel and we propose that it is located within the task-conflict to response connection, adding to a growing body of literature that acknowledge the functional significance of the hyperdirect pathway in cognitive and motor control (Brittain et al., 2012; Cavanagh et al., 2011; Davelaar, 2009; Frank, 2006). Second, of the two noise sources, task-demand noise affects predominantly the color words. This analysis has two consequences: (1) task-demand noise is the source for the reverse *SD* pattern ($SD_{neutral} < SD_{congruent}$), and (2) the comparison of $SD_{congruent}$ versus $SD_{nonword\text{-}neutral}$ might be used as a proxy for variability in proactive task control.

AQ: 4

Finally, we note that without the task-conflict to response inhibition (for the same set of parameters as in the simulation in Figure 10), we obtain a speedup in the congruent and incongruent (but not in the neutral) conditions, together with a decrement in accuracy (of 97%) in the incongruent condition. A further reduction of the PC-parameter to .085, results in a more marked decrement in the incongruent accuracy (at 90%), with an interference that is not changed, but with a positive facilitation score ($RT_{congruent} < RT_{neutral}$). We delay discussion of this result to the Schizophrenia subsection of the General Discussion (see also the online supplementary material).

General Discussion

The Stroop task is one of the most commonly used measures of attentional control (MacLeod, 1991). Here we reviewed recent work that indicates an important source of variability in the deployment of attentional control—task conflict and its resolution. We proposed the PC-TC model that extends the previous Stroop control models of Cohen, Botvinick and colleagues to account for the variability caused by these factors.

The PC-TC Model

Task conflict is an important psychological process, which occurs within the Stroop task when a stimulus activates two competing task sets in the absence of robust proactive control; such robust control would prevent task conflict from emerging in the first place, or if it emerged, it would allow it to be rapidly resolved (Figure 6A, top left). When task conflict emerges and before it is resolved, responses are withheld, resulting in a RT-slowdown. Because task conflict emerges for color words (congruent or incongruent Stroop stimuli) and neutral words, but not for nonword neutral Stroop stimuli, the RT-slow down affects congruent and incongruent Stroop stimuli, but not nonword Stroop neutrals. The specific slowdown of congruent Stroop trials compared with nonword neutral trials results in a Stroop-RF effect, which is a signature of task conflict and is associated with reductions in proactive control.

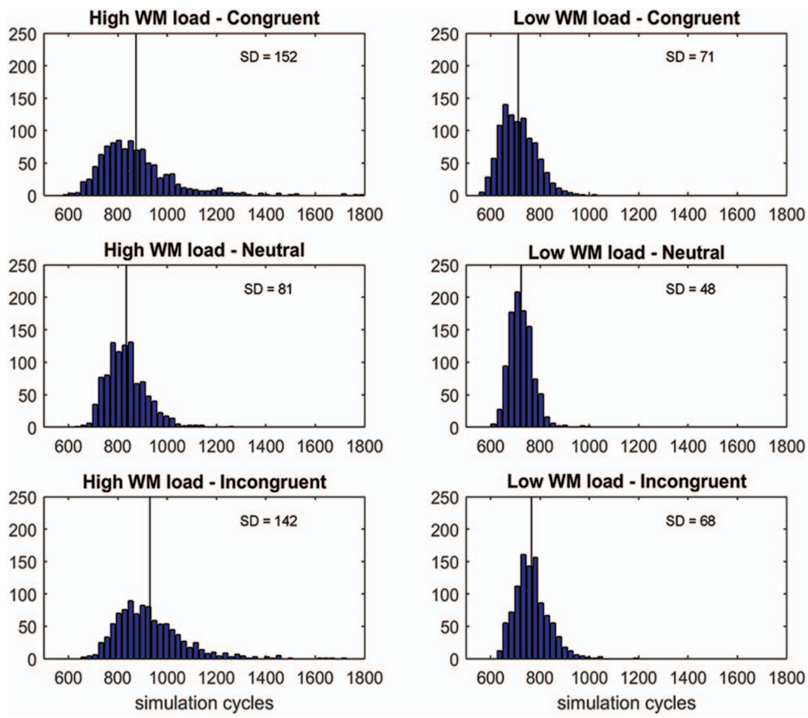

Figure 10. Reaction time (RT) distributions (and mean-line) for the stochastic model with noise at the level of task demand units and response units fitted to the working memory (WM) load data (Kalanthroff, Avnit, Henik, Davelaar, & Usher (2015). See the online article for the color version of this figure.

We have reviewed an extensive literature that shows how the variability in attentional control, as indicated by the Stroop-RF effect, is associated with experimental manipulations that affect proactive control. Such manipulations involve the frequency of nonword Stroop stimuli (Entel et al., 2015) and the presence of Stroop cues (e.g., Goldfarb & Henik, 2007), the load of a concurrent working memory task (Kalanthroff, Avnit, et al., 2015), and cue-target intervals (Kalanthroff & Henik, 2014). In addition, the Stroop-RF effect is subject to individual differences in the ability to deploy control (e.g., Kalanthroff & Henik, 2014; Parris, 2014).

To account for this variability in Stroop RF, we have proposed a Stroop model, which we label the PC-TC (proactive-control,

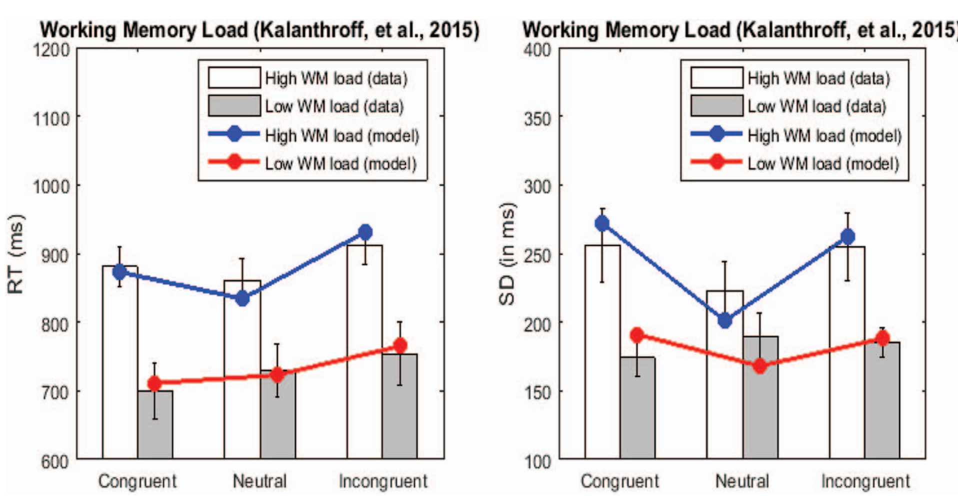

Figure 11. Fits of the stochastic model to the Kalanthroff, Avnit, Henik, Davelaar, and Usher (2015) working memory (WM) load data. Left panel: Empirical data and fits to mean reaction time (RT). Right panel: Empirical data of and fits to the within-subject standard deviation of RT. In both panels we assume intercepts, which correspond to a residual time (374 ms) and its variability (SD = 120 ms). See the online article for the color version of this figure.

task-conflict) model. The PC-TC model is related to a broad computational framework of attention control recently proposed by Braver (2012)—the dual mechanism of control (DMC). As in a previous DMC model (De Pisapia & Braver, 2006), the PC-TC model assumes two modes of attentional control—proactive and reactive. The PC-TC model, however, differs from the DMC model in its implementation of the reactive control process. In the DMC, reactive control is triggered by the detection of information conflict. In contrast, in PC-TC reactive control is triggered by weak proactive control processes that interact with the bottom–up activation triggered by the stimulus to bias a 'winner take all' competition in favor of the relevant task demand. Hence, the PC-TC model allows us to account for the RF effects that appear in tasks with reduced proactive control.[3] As we have shown, the PC-TC model was able to provide qualitative and quantitative fits to the reviewed data. Fn3

An additional advantage of the PC-TC model is its ability to cope with an important criticism raised against similar Stroop models. As discussed in detail by Mewhort et al. (1992), an influential Stroop model based on the top–down modulation of processing by contextual task demand representations (Cohen et al., 1990) accounts well for mean RT, but makes incorrect predictions regarding RT-variance. It predicts that RT-variance is larger in neutral compared with congruent trials, contrary to the data. Here, we showed that the PC-TC model makes the correct qualitative prediction on the RT-variability of Stroop conditions, once noise is introduced at the task-demand level. Critically, the PC-TC account is intrinsically related to the noise in the generation of task conflict—the central component of the model—which affects congruent and incongruent Stroop trials but not nonword neutral trials.

Below, we discuss a number of implications of the PC-TC model for the theoretical understanding of Stroop data in control and in clinical populations, as well as a number of limitations and potential extensions.

What Does the Stroop Effect Measure?

Both informational- and task-conflict slow down responding in the Stroop task. In addition, they interact in a subtle way. Because incongruent Stroop stimuli suffer from both types of conflicts, while congruent stimuli suffer from task-conflict only, one usually uses the total Stroop effect (RT difference between incongruent and congruent conditions) as a measure of informational conflict. This is a valid operational definition, however, only under the assumption of additivity in the slowdown caused by the two conflict types. Although this assumption works reasonably, under the standard Stroop conditions (high-PC and low task-conflict), it does not when task conflict is elevated (low-PC). In such conditions, the Stroop effect does not provide a clean measure of informational conflict. This is due to the overlap in the processes that resolve the two types of conflict—a type of subadditivity.

To illustrate, consider the effects of a concurrent working memory load on Stroop RT. As shown in two articles (Kalanthroff, Avnit, et al., 2015; Soutschek et al., 2013), the increase in load results in a slowdown for both congruent and incongruent Stroop stimuli, without an increase in the Stroop effect (calculated as incongruent minus congruent RT; see Figure 8, bottom left). The lack of change in the Stroop effect could lead one to conclude that working memory load did not affect the information conflict; however, our model suggests a different explanation. According to the PC-TC model, the slowdown of the two processes is subadditive (the informational and task conflict resolution processes overlap in time) and therefore the slowdown in the incongruent condition due to load is not much larger than the slowdown in the congruent condition. This does not mean, however, that the load had no effect on the information conflict. Rather, what the model suggests is that the load slows down the congruent condition due to task conflict resolution, and it slows down the incongruent condition due to resolving temporally overlapping task conflict and informational conflict.

Dissociations Between Stroop Measures

The Stroop effect ($RT_{incongruent} - RT_{congruent}$) and the interference effect ($RT_{incongruent} - RT_{neutral}$) are the most frequently used Stroop measures, which are assumed to probe informational conflict. However, our discussion above suggests that this is only warranted in situations in which the task-conflict is negligible—high PC. Under low PC conditions, as task and information-conflict resolution overlap in time, the total Stroop effect, may underestimate informational conflict, explaining why a number of manipulations that are expected to increase information conflict, such as WM-load, appear to show null effects on the total Stroop measure, but they show marked changes in the facilitation scores (Kalanthroff, Avnit, et al., 2015; Soutschek et al., 2013; see Figure 8).

In particular, the PC-TC model predicts that the Stroop facilitation effect and the overall Stroop effect can be correlated positively, negatively, or show no correlation. To demonstrate this, we plot in Figure 12 the total Stroop effect (top panel) and Stroop facilitation (bottom panel) for a wide range of PC values and for values of task-demand inhibition (between the two task demand units), illustrated by the colored lines, which produced the best fits to the data in Figure 8. For reference, we also include the best-fitting parameter combinations as dots in the graphs. As shown (and illustrated via the red, green and blue dots), the general trend is that the Stroop effect increases when the level of proactive control decreases and a parallel effect can be seen in the facilitation score (more RF with decreasing PC). However, in the part of the parameter space with high levels of PC and low levels of task-demand inhibition, the Stroop facilitation effect and the total Stroop effect show a different pattern. Although the RF increases with decreasing PC (under these conditions too), the total Stroop effect remains roughly constant, as illustrated in the WM-load manipulation (dots on the cyan line; the task-demand parameter values are shown in the legend). F12

To better illustrate this dissociation between the facilitation effect and the Stroop effect and to make some experimental predictions, we plot in Figure 13, the Stroop facilitation and the Stroop effect against each other. The black-star denotes the combination of effects with the highest PC level and the various color lines correspond to different levels of task-demand inhibition (between the two task demand units). All five lines springing from this location follow a decreasing PC gradient F13

[3] We could not have done this if we conditioned reactive control on informational conflict (De Pisapia & Braver, 2006), which is minimal for congruent trials.

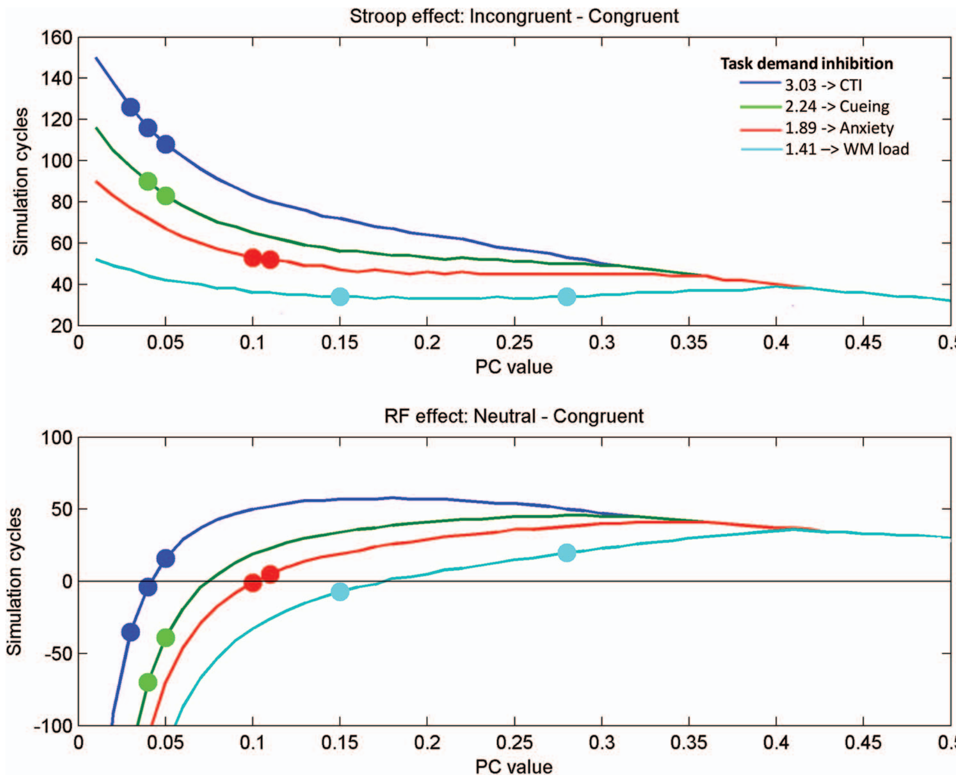

Figure 12. Stroop effect (top panel) and Stroop facilitation effect (bottom panel) for a wide range of proactive control (PC) values and for values of task-demand inhibition (between the two task demand units) that were shown to produce the best fits to the data in Figure 8 (the task-demand parameter values are shown in the legend). Colored dots represent the best-fitting proactive control PC parameter values to the experimental conditions. See the online article for the color version of this figure.

toward the bottom of the figure. We see that for task-demand inhibition values that correspond to the magenta and cyan lines (the lines on the left in the figure), decrease in PC leads to a consistent decrease in Stroop facilitation accompanied by fragile and inconsistent Stroop effects. For task-demand inhibition values that correspond to the red, green and blue lines, decrease in PC results in a consistent increase in the Stroop effect, accompanied by fragile and inconsistent Stroop facilitation effect. Not all combinations of changes in Stroop facilitation and in total Stroop effect are predicted. For example, the model does not predict the hypothetical pattern in which with decrease in PC, Stroop facilitation increases while the Stroop effect decreases (a pattern that was never documented in the literature), indicating that the model is not overflexible.

Another factor that can generate a dissociation between the total Stroop effect and the facilitation score is the level of the task-conflict to response inhibition. As shown in Figure 7 (red vs. blue curves), changes in the level of PC, have different effects on the two measures, in the intact model (with task-conflict to response inhibition in place), but not in the model that is lacking this task-conflict inhibition component. In the following section, we discuss in detail how this dissociation plays a major role in explaining differences in Stroop patterns between controls and three types of patient populations: OCD, schizophrenia, and anxiety.

Implications for Understanding Clinical Populations

Examining Stroop deficits in clinical populations provides a special opportunity to observe dissociations between various Stroop measures and to understand the nature of the control deficits that affect the patients. Here we review three main pathologies: OCD, schizophrenia, and anxiety, which have been implicated in expressing a reduction in the ability to carry out goal-driven behavior and a shift toward automatic patterns. Yet, as we show below, the behavioral patterns that these patients' populations show is different, and can be naturally accounted for in the PC-TC model.

Obsessive–compulsive disorder (OCD). OCD is a highly debilitating disorder (affecting 2–3% of the population) characterized by distressing recurrent intrusive thoughts (obsessions) and repetitive behaviors or mental acts that the person feels compelled to perform (compulsions; Huppert, Simpson, Nissenson, Liebowitz, & Foa, 2009). The notion that impairment in proactive task control plays a crucial role in OCD resonates with previous findings in the literature and several researchers have suggested that difficulties in inhibiting behaviors that are triggered by stimuli, which automatically potentiate unwanted motor responses, underlie the phenomenology of OCD. For example, Gillan et al. (2011) found that OCD patients rely more on "automatic stimulus-driven behaviors . . ." (or habits; Gillan et al., 2015, p. 284) due to

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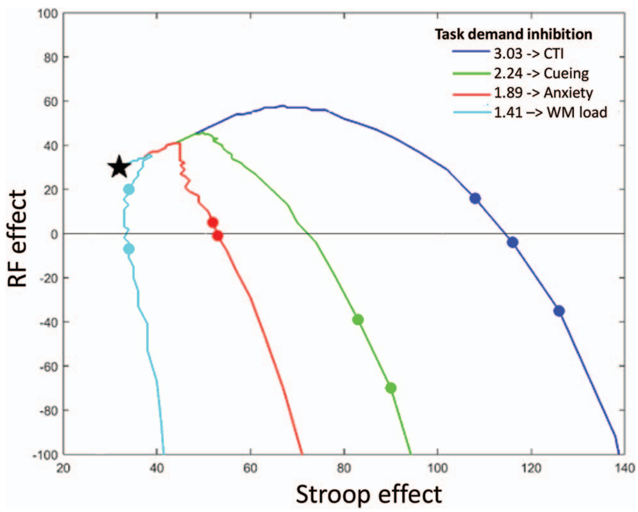

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Figure 13. Stroop facilitation and the Stroop effect plotted against each other. Each line corresponds to a different level of task-demand inhibition (between the two task demand units), as obtained by fitting the data in Figure 8 (the task-demand parameter values are shown in the legend). The dots correspond to best-fitting parameters to the experimental conditions. The black-star denotes the location with the highest proactive control (PC) level. All lines coming from this star follow a decreasing PC gradient towards the bottom of the figure. See the online article for the color version of this figure.

impairments in their goal-directed system (see also Gillan & Sahakian, 2015).

In two recent investigations, we found additional indications for deficient proactive task control in OCD patients. In a first study (Kalanthroff, Anholt, & Henik, 2014), we administered two blocks of the Stroop task: a standard block (33% neutrals) and a low control block (75% neutrals). In the standard (but not in the low-control) block we found a smaller Stroop facilitation effect in OCD patients than in healthy controls, but no difference in the overall Stroop effect. Moreover, unlike the healthy controls who show differences in the Stroop facilitation effect as a function of block changes in the frequency of neutral trials, OCD patients appear invariant to this manipulation, showing the same level of facilitation score at all levels of neutral-frequency levels. This result is predicted by our model, under the assumption that OCD patients have a deficit in the ability to deploy PC. Indeed, as illustrated in Figure 12 (bottom panel), across all the lines that reflect differences in the task-demand inhibition, lower PC-level lead to a reduction in the facilitation score (all lines intersect the zero-axis). Furthermore, if the time to resolve task-conflict depends on the PC-level that participants deploy to the task, and if this level is already deficient in OCD patients, this can explain why manipulations such as variations in neutral frequency have no further impact on the Stroop pattern (e.g., no effect on the overall Stroop effect).

In the second study, we showed that a computerized training program that targets proactive task control (using an adapted version of the stop-signal task) is effective in improving OCD symptoms (>35% reduction in symptom severity; Koran, Hanna, Hollander, Nestadt, & Simpson, 2007) in treatment refractory OCD patients (Kalanthroff, Steinman, Schmidt, Campeas, & Simpson, 2017). In addition, compared with baseline, at the end of the study RTs for Stroop congruent and incongruent (but not for neutral) trials were significantly faster. These results support the theory according to which failure to suppress irrelevant stimulus-driven behaviors as a result of reduced proactive task control maintenance is a pathological trait that also constitute a fundamental characteristic of the inability to suppress compulsive behaviors in OCD (e.g., Anholt, Linkovski, Kalanthroff, & Henik, 2012; Chamberlain, Blackwell, Fineberg, Robbins, & Sahakian, 2005; Kalanthroff, Anholt, et al., 2013; Robbins, Gillan, Smith, de Wit, & Ersche, 2012).

Schizophrenia. Schizophrenia is a major psychiatric disorder (affecting 1% of the population), which is also strongly associated with deficient proactive task control (Braff, 1993; Cohen & Servan-Schreiber, 1992, 1993; Kurtz, Moberg, Gur, & Gur, 2001; Liu et al., 2011) and which played a major role in the development of Stroop modeling (Cohen & Servan-Schreiber, 1992, 1993; Cohen, Braver, & O'Reilly, 1996). The traditional account is that patients with schizophrenia have a reduced ability to use task context in order to inhibit automatic responses, yet, this only partially accounts for the behavioral and neural data. Studies that used the Stroop task report that patients with schizophrenia have a normal interference effect ($RT_{incongruent} - RT_{neutral}$), an enlarged facilitation ($RT_{neutral} - RT_{congruent}$) effect, and an increased error rate in the incongruent condition. These finding are robust (for reviews see Barch et al., 1999; Henik & Salo, 2004). In other words, in terms of RT, patients with schizophrenia do not show clear signs of deficient inhibition and they even perform better than normal in the congruent condition. In accuracy rates, on the other hand, these patients exhibit difficulties in incongruent trials.

The PC-TC model provides a natural account of this specific Stroop pattern, under the assumption that the schizophrenia deficit involves a difficulty in detecting task-conflict, in addition to the reduced capacity in the maintenance and use of task-context (Cohen & Servan-Schreiber, 1992). A schizophrenic-deficiency in detecting task conflict is also supported by the difference in ACC activation between incongruent and neutral trials (i.e., the interference effect), which is smaller in people with schizophrenia than in healthy participants (Carter, Mintun, Nichols, & Cohen, 1997). Given the known role of the ACC in conflict detection (e.g., Botvinick et al., 2001; Braver et al., 2001; Carter et al., 1998), these findings suggest that the ability of the ACC to detect conflict is damaged in patients with schizophrenia (see also Braver, Barch, & Cohen, 1999; Dolan et al., 1995; Goldfarb, 2017; Kerns et al., 2005).

We ran a simulation with the PC-TC model, with the same parameters to those in Figure 10, except for a reduced PC-value (.085) and without the task-conflict to response inhibition. The results demonstrate a reduced accuracy in the incongruent condition (90%, as in the data of Barch et al., 1999), together with a marked increase in the Stroop facilitation effect and no change in Stroop interference effect (see the online supplementary material for details). This result can be understood to follow from the lack (or reduction) of task-conflict, which facilitates RT in the congruent and incongruent condition as the system does not waste time on resolving this conflict, resulting in enhanced facilitation and preserved interference in RT. This, however, has the cost of a reduced accuracy in the incongruent condition, as the response is generated before the task-control to the relevant (color) dimension is restored. Note also that when the control mechanism fails to detect the task conflict in the congruent condition, it does not produce errors.

Anxiety disorders and emotional distractors. Cognitive load is expected to reduce resources for cognitive control (e.g., de Fockert et al., 2001), and emotional distractors have been shown to disrupt working memory capacity (Denkova et al., 2010; Dolcos & McCarthy, 2006). Within the Stroop framework, brief emotional distracters (aversive IAPS pictures) were shown to disrupt proactive control in healthy participants in some studies (Hart, Green, Casp, & Belger, 2010) but not in others (Kalanthroff et al., 2016). However, when carrying out the same tasks on a group of participants with high anxiety, we found a clear effect of emotional distracter (aversive compared with neutral prime pictures) on the Stroop proactive control (Kalanthroff et al., 2016). As predicted by the PC-TC model, this led to an increase in Stroop interference and critically a Stroop RF (see Figure 8, bottom right); there was a slowdown in both congruent and incongruent but not in neutral Stroop trials. Similarly, Kalanthroff et al., 2017 found attenuated proactive task control (i.e., larger Stroop interference effect, marginally significant smaller Stroop facilitation effect, and an object-interference effect) following a threatened morality manipulation, in which participants were asked to write about an immoral deed they had committed (Zhong & Liljenquist, 2006). It is interesting to note that this detrimental effect on proactive control was eliminated following a simple wiping of hands. These results are consistent with the Dual Competition Model (Pessoa, 2009; see also an explicit computational model (Wyble et al., 2008) in which the emotional pathway inhibits proactive control in the Stroop task), and with the attentional control theory (Eysenck, Derakshan, Santos, & Calvo, 2007). The former predicts a competition between proactive task control and emotional processing, whereas the latter suggests that subjects who suffer from anxiety are unable to resolve this competition in favor of the proactive task control due to a tendency to decrease top–down regulation. These findings shed new light on the effect of negative emotions on cognitive control: Although healthy participants are able to ignore (inhibit) the irrelevant emotional primes, people who suffer from anxiety are more affected by the negative stimuli, resulting in a reduction of proactive control, as indicated by increased interference and RF. Thus, the combination of irrelevant emotion stimuli and anxiety interferes with the ability to manage a task correctly and adaptively.

Model Predictions

The PC-TC model we have proposed allows us to make a number of predictions to conditions that were not part of its original design. Although the model was developed to account for the variability in Stroop RF at the level of mean-RT, it also makes a number of additional predictions. First, the model accounts for the pattern of increased RT-variability (within participants) in congruent and incongruent, compared with neutral Stroop trials, which was a serious challenge for the Connectionist Stroop model (Mewhort et al., 1992). Second, as shown in the online supplementary materials, the model predicts that RF increases when the response threshold decreases. Thus, manipulations of response caution should affect the magnitude of the RF. Third, the model was able to account for deficits in patient populations, such those found in OCD, schizophrenia, and anxiety disorders (Figure 8, bottom right). Future experiments can probe how the Stroop facilitation and interference scores in patients with schizophrenia are affected by manipulations that usually result in a reduction in proactive control (e.g., proportion of neutral Stroop trials), and thus increase the observed expression of task conflict.

Furthermore the conceptual framework of the model, can drive predictions to tasks that share processes (but are not identical to) the Stroop task. One such example is the object interference task, in which participants are asked to name the color of an abstract form or a nameable object (Prevor & Diamond, 2005). This task is analogous to Stroop, as far as it has two competing processes: naming the color (task-relevant) versus naming the object (automatic), and the two types of stimuli (abstract form vs. namable objects), which correspond to types of neutral in Stroop (nonword vs. word-neutrals). As shown by La Heij and colleagues, objects exogenously trigger an associative-automatic object-naming task that competes with the relevant endogenously activated color-naming task, resulting in longer RTs to nameable objects compared with abstract forms—the so-called "OI effect" (e.g., La Heij & Boelens, 2011; Prevor & Diamond, 2005). According to these researchers, "when a colored picture is presented for color naming, endogenous control (the intention to name the color) has to overrule exogenous control (the picture activating the incorrect task of object naming)" (La Heij, Boelens, & Akerboom, 2013, p. 79). In healthy individuals, the OI effect occurs only with young children (until the age of 6[1/2] years old), as older children and healthy adults are able to efficiently solve the task conflict very quickly by virtue of efficient task control (La Heij & Boelens, 2011).

The PC-TC model, although not designed for this task, can naturally be extended to explain the OI-effect. To achieve this, we only need to replace the word-reading unit with an object-naming one, and to assume that objects exogenously activate this unit, triggering task-conflict and thus slowing down responses in situations with low-PC (children). Furthermore, the PC-TC model predicts that any manipulation that reduces PC-control will potentially lead to behavioral manifestation of task conflict—the OI effect—even in healthy adults. For example, manipulations that usually affect proactive control (e.g., concurrent WM load, task switching, or changes in the proportions of abstract forms compared with namable objects) will result in a larger task conflict and hence to an OI effect. Similarly, we predict that an OI-effect will emerge in standard OI-tasks (i.e., without manipulations that reduce control) in clinical populations, such as OCD, who suffer from a deficit in deploying proactive control (see Kalanthroff, Henik, et al., 2017), but not in people with schizophrenia, if they indeed have a deficit in detecting task-conflict (Goldfarb, in preparation; note that the OI effect is caused by task-conflict rather than lexical competition (LaHeij et al., 2010).

Limitations and Future Work

Other factors that determine PC: Associative learning and unique S-R associations. In the model we presented, we accounted for how the variability in PC affects the way in which

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the participants carry out a particular Stroop trial. A more complete model needs to close the loop by determining how various variables of the task (over a trial or a block) determine the level of proactive control. Here we relied on the conflict adaptation model (Botvinick et al., 2001), which assumes that proactive task control is a function of informational conflict. For example, we have assumed that the level of PC is reduced in a block with a high frequency of neutrals (compared with a low frequency of neutrals) as a result of the reduced informational conflict.

More recent findings, however, indicate that information conflict is not the only factor that affects the level of proactive control. In a series of recent studies that examined the impact of list-congruency proportion on the list- versus item-specific task control, Bugg and colleagues reported important boundary conditions for the presence of list-level task control (Bugg, 2014; Bugg et al., 2011). As suggested by Bugg (2014), list-level control—which is proactively deployed before the specific item is processed—depends not only on the presence of high information-conflict (a high proportion of incongruent trials), but also on the absence of reliable S-R associations that link
Fn4 word stimuli to unique incongruent colors[4] (word *RED* always in blue color; for the impact of the correlation between color and word stimuli on the Stroop effect see also Melara & Algom, 2003; Sabri, Melara, & Algom, 2001).

A more complete model should therefore include the loop from conflict detection (possibly gated by the detection of reliable S-R associations) to task control on a trial-by-trial basis. Furthermore, the conflict adaptation model (Botvinick et al., 2001) may be extended to depend on both informational and task conflict (Levin & Tzelgov, 2014; see below). As suggested by Levin and Tzelgov, the present control models assume that only informational conflict affects proactive task control, neglecting the potential role of task conflict. Such a model should also account for interaction patterns that are obtained between manipulations that vary task conflict (frequency of neutral trials) and those that vary informational conflict (proportion of incongruent trials; Entel et al., 2015).

The PC-TC Model Implementation

The PC-TC model captures a number of data sets showing RF. It does this by computing task conflict and by using this signal to delay responding. An important question is whether other mechanisms that are already part of the Stroop model architecture could account for changes in facilitation (and for RF). A first suggestion is the inhibition between task demand units. Based on our explorations, this factor does not capture the data in the absence of the task-conflict to response inhibition. Increasing the task-demand inhibition (between the two task demand units) leads to a faster resolution of task uncertainty, whereas decreasing it, allows the task-irrelevant (word-reading) unit to exert top–down influence. In order to check if these conclusions are contingent on our specific Stroop model implementation, we also simulated the GRAIN-Stroop model described in Botvinick et al. (2001; see also Cohen & Huston, 1994), with its original parameters (see the online supplementary martial). We were unable to obtain RF for any value of task-demand inhibition; in fact, a robust Stroop facilitation (as found in schizophrenia), appears to be the characteristic signature of the GRAIN Stroop model, in absence of task-conflict to response inhibition. The reason for this is that the indirect inhibition from word units (via task demand) to color units is weaker than the direct excitation between the word units and response units (see Figure S4 in the online supplementary martial).

A second factor to consider is the way we implemented task-conflict resolution. The PC-TC model implements a passive type of conflict resolution in so far as that during the interval in which the response layer is inhibited by task conflict, the competitive dynamics in the task-demand layer resolve the competition with the help of the weak PC bias. Thus, although the amount of PC remains constant (see Figure 5) within a trial, the effective control signal increases as a result of the competition between the task-demand units (red line, in Figure 6,first column). We have decided to keep PC constant within a trial, as our focus was on variations of proactive control on a slower time scale (Botvinick et al., 2001). Another possibility, which may be explored in future studies, is to use task conflict to modulate the proactive control unit (Levin & Tzelgov, 2014). These types of more active *reactive control* processes could exert their effects within the same trial (Davelaar, 2008). This is somewhat similar to the DMC model of Stroop (De Pisapia & Braver, 2006), except that the latter uses information conflict to drive a separate task control representation. Alternatively, one can extend the model so that task conflict in one trial affects, together with informational conflict, the proactive control in the next trial (Botvinick et al., 2001). Finally, one can extend the model to include associative learning between colors and words that reflect task correlations (Melara & Algom, 2003), and the detection of reliable S-R associations (Bugg, 2014). Such an implementation would allow investigations of within-block variability of proactive control. These different implementations of conflict monitoring and temporal dynamics of conflict resolution will need to be explored in future computational work.

Conclusions

We reviewed data that shows variability in Stroop facilitation (which taps into task-conflict) and which dissociates, under some conditions, from the variability in the total Stroop effect (associated with information-conflict). Based on this we presented a model which includes task-conflict resolution in the framework of the control-Stroop model (Botvinick et al., 2001). This model, not only accounts for qualitative and quantitative data patterns on mean-RT but also for patterns of RT-variability (standard deviation of RT larger in congruent vs. neutral conditions; Mewhort et al., 1992). Finally, the model makes predictions for dissociations between Stroop measures that are obtained in patient populations, such as people with OCD and schizophrenia.

[4] This theory is called AACT, which stands for Association as Antagonists to Top–down Control (Bugg, 2014).

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