



## Original Articles

## Is adaptive control in language production mediated by learning?

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## ARTICLE INFO

## Keywords:

Word production  
Language monitoring  
Cognitive control  
Domain generality  
Congruency sequence effect (CSE)  
Conflict adaptation, learning

## ABSTRACT

Recent work using the Picture Word Interference (PWI) paradigm has revealed that language production, similar to non-verbal tasks, shows a robust Congruency Sequence Effect (CSE), defined as a decreased congruency effect following incongruent trials. Although CSE is considered an index of adaptive control, its mechanism is debated. In two experiments, we tested the predictions of a learning model of adaptive control in production, using a task-switching paradigm fully balanced to evaluate CSE on a PWI trial as a function of the congruency of a 2-back PWI trial (within-task CSE), as well as a 1-back trial belonging to a different task (cross-task CSE). The second task was a visuospatial task with congruent and incongruent trials in Experiment 1, and a self-paced reading task with ambiguous and unambiguous sentences in Experiment 2 that imposed a gap between the two PWI trials twice as long of that in Experiment 1. A learning model posits that CSE is the result of changes to the connection weights between task-specific representations and a control center, which leads to two predictions in our paradigm: (a) a robust within-task CSE unaffected by the intervening trial and the gap duration, and (b) an absent or reversed cross-task CSE. These predictions were contrasted with two versions of an activation model of CSE. In accord with the predictions of the learning model, we found robust within-task CSE in PWI in both Experiments with a comparable effect size. Similarly, evidence of within-task CSE was also found in the visuospatial and sentence reading tasks. On the other hand, examination of cross-task CSE from PWI to the other tasks and vice versa revealed either absent or reversed CSE. Collectively, these results support a learning model of adaptive control in language production.

## 1. Introduction

Cognitive control can be defined as operations required to resolve competition in favor of the most goal-appropriate response. The importance of cognitive control in language production has been implicitly acknowledged since early psycholinguistics research, in which it was shown that simultaneous activation of competing lexical representations was a natural product of spreading activation in a highly interconnected system (e.g., Dell, 1986). But compared to other cognitive areas, study of cognitive control in language production did not gain much attention until recently, perhaps partly due to the proposal of non-competitive accounts of lexical selection (e.g., Mahon, Costa, Peterson, Vargas, & Caramazza, 2007). However, in recent years, a series of studies have demonstrated the true susceptibility of the language production system to interference during both semantic–lexical (e.g., Belke, Meyer, & Damian, 2005; Costa, Alario, & Caramazza, 2005; Schnur, 2014; Schnur et al., 2009) and lexical–phonological mapping (Breining, Nozari, & Rapp, 2016; Nozari, Freund, Breining, Rapp, & Gordon, 2016; O'Seaghdha, & Marin, 2000; Sadat, Martin, Costa, &

Alario, 2014), inciting new interest in mechanisms that resolve such interference. Two sets of such studies have investigated such mechanisms: one set comprises studies that have reported a correlation between production performance (e.g., picture naming latencies or production errors) and performance on inhibitory control tasks (Shao, Meyer, & Roelofs, 2013; Shao, Roelofs, Martin, & Meyer, 2015; Shao, Roelofs, & Meyer, 2012; Trude & Nozari, 2017). The second set comprises lesion studies that have linked a cortical region such as the lateral prefrontal cortex, usually considered important for competition resolution, to performance on a production task that requires resolution of lexical competition (e.g., De Zubicaray, McMahon, Eastburn, & Pringle, 2006; Piai, Riès, & Swick, 2016; Piai, Roelofs, Acheson, & Takashima, 2013; Riès, Karzmark, Navarrete, Knight, & Dronkers, 2015; see Nozari & Thompson-Schill, 2015, for a review).

While these studies have been critical in demonstrating the importance of cognitive control in language production, they mostly rely on indirect demonstrations of the need for, or the implementation of, control in production. It is thus difficult to establish a causal role between control and production abilities, or to understand how

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fluctuations in control demands lead to regulations of control in order to optimize performance. This regulatory process, called “adaptive control”, can be studied by investigating how performance on a demanding trial changes future performance on a trial with similar demands. Gratton, Coles, and Donchin (1992) were the first to report such a change, by showing a decrease in the size of the Flanker effect (defined as the difference in accuracy or response times between incongruent and congruent trials) after an incongruent compared to a congruent trial. The “Gratton effect” was later replicated in other tasks such as the Simon task (e.g., Stürmer, Leuthold, Soetens, Schröter, & Sommer, 2002), and the button-press Stroop task (e.g., Kerns et al., 2004), and received the more general label of “congruency sequence effect” (CSE) that we opt to use throughout this paper. CSE paradigms are currently the gold standard for examining adaptive control.

Recently, we and three other research groups have successfully replicated the canonical CSE pattern in word production using the Picture-Word Interference (PWI) paradigm (Duthoo, Abrahamse, Braem, Boehler, & Notebaert, 2014; Freund, Gordon & Nozari, 2016; Shitova, Roelofs, Schriefers, Bastiaansen, & Schoffelen, 2017; Van Maanen & Van Rijn, 2010). In this paradigm, participants must name a picture with a word superimposed on it. On congruent trials, the word is the name of the picture. On incongruent trials, the word is a different name (often a semantic competitor of the picture; Schriefers, Meyer, & Levelt, 1990). The congruency effect manifests as lower accuracy and/or longer RTs on incongruent compared to congruent trials, and CSE is defined as a reduction of the congruency effect after incongruent trials. This finding is exciting because it demonstrates that word production in the presence of competitors can be regulated online, just like non-linguistic tasks such as arrow Flanker and Simon tasks. More importantly, it opens a promising avenue for studying the nature of cognitive control processes that operate in language production. Our interest is in the mechanism by which CSE is generated in language production. Specifically, we test whether a learning account of CSE is suitable for implementing adaptive control in word production.

### 1.1. Accounts of CSE

Three classes of accounts—*associative*, *control-based*, and *hybrid*—have been proposed to explain CSE. Associative accounts view CSE as a consequence of forming specific associations between response choices and physical stimulus properties. The most prominent account is “feature integration” (Hommel, Proctor, & Vu, 2004), which proposes the binding of co-occurring features (e.g., blue hue + word “red” + evoking the left response button) as an “event file” in episodic memory. When any of the features are repeated on a subsequent trial, the entire memory is retrieved. Processing is facilitated if the new event has complete overlap with the previous one (i.e., if it is the exact same trial). Partial overlap between the previous and the new event, on the other hand, hinders performance, as the binding needs to be undone in order for the memory to be updated (Mayr, Awh, & Laurey, 2003). Associative accounts successfully explain CSE in tasks with a small stimulus or response sets, in which the probability of feature overlap from one trial to the next is high.

However, CSEs have also been observed in the absence of feature overlap and other low-level confounds. Memory confounds are usually controlled for by increasing the stimulus set size (often from two to four) to increase the number of unique combinations. This solution, however, creates a new problem in which the probability of each congruent stimulus is higher than each unique incongruent stimulus. For example, in order to maintain a 1:1 ratio of congruent and incongruent trials in a four-choice Stroop task, the trial of “red” + red (i.e., “word” + hue) must happen four times more frequently than “red” + blue, “red” + green, and “red” + yellow. The emergence of CSEs under these circumstances may reflect the learning of these contingencies (Mordkoff, 2012; Schmidt & De Houwer, 2011). Importantly, though, when controlling for both memory confounds and contingency

learning, CSEs have still been observed (Freitas & Clark, 2015; Hengstler, Holland, Steenbergen, & Knippenberg, 2014; Kunde & Wühr, 2006; Weissman, Egner, Hawks, & Link, 2015; see Egner, 2014 for a review). Thus, associative accounts alone are insufficient to explain the CSE.

In contrast to associative accounts, control-based accounts propose the effect is driven by abstract control processes that operate independently from stimulus features. The common feature of control-based theories is their assumption that the CSE is driven by dynamic adjustments in top-down control, regardless of the specific nature of the representations involved in the task. The original control-based account of CSE is grounded in the modulation of expectations (Gratton et al., 1992), and assumes that individuals typically expect events to repeat in time. This expectancy-based account thus posits that encountering an incongruent trial generates an expectation (and ensuing preparation) for a subsequent incongruent trial, and it is this preparation that generates the CSE. A second influential control-based account, the conflict-based account, proposes that the adjustment of top-down control is mediated by monitoring the level of conflict on each trial (Botvinick, Braver, Barch, Carter, & Cohen, 2001). When conflict is high (i.e., in an incongruent trial), a signal is sent to recruit more control. This control, in turn, benefits performance on a subsequent high-conflict (incongruent) trial. The conflict-based account has had success in explaining a wide range of CSE, but has been criticized by Lamers and Roelofs (2011), who found larger CSE for post-congruent trials compared to both post-incongruent and post-neutral trials. These authors argued that a conflict-based account would have predicted differences between the post-incongruent and post-neutral trials.

While there is abundant evidence for a CSE in the absence of low-level feature overlap or contingency learning (see above references), there is little doubt that feature overlap enhances the CSE (Hommel, 1998; Nieuwenhuis et al., 2006; Notebaert, Gevers, Verbruggen, & Liefoghe, 2006). This finding has prompted hybrid accounts of the CSE, which posit an interaction between top-down control mechanisms and bottom-up stimulus features. The most prominent hybrid account is the “adaptation-by-binding” model (Verguts & Notebaert, 2008, 2009), which proposes that conflict is used as a signal to increase the weights between stimulus features and attentional units that maintain task goals, through Hebbian learning. How abstract these stimulus features should be is less clear. While the adaptation-by-binding model is implemented on low-level features, Egner (2014) argues that such learning must include more abstract features. Critically, though, both Egner (2014) and Verguts and Notebaert (2008, 2009) view adaptive control as a learning mechanism.

### 1.2. Testing a learning account of CSE in word production

We use the general framework of Verguts and Notebaert’s (2008) adaptation-by-binding model to discuss the key predictions of a learning model of adaptive control. Many aspects of this model are not critical to our purpose, so instead of presenting the model in full detail, we will focus on the main mechanism and adapt it to our current purpose. The left panel of Fig. 1 shows a schematic of this model. At a general level, the model includes two sets of representations: task-specific representations (e.g., color representations, orthographical representations), and task demand units, which implement top-down control over task-specific representations in order to maintain task goals (e.g., “name the color/do not read the word” in a Stroop task). We use the label “Control center” instead of “task demand units” to cover a broader range of top-down control operations, such as resolving competition during lexical selection in PWI. Similarly, task-specific representations can be extended to include task-specific operations, such as mapping of semantic features to lexical items.

The black arrow indicates the locus of the CSE in the model: after each trial, the model “learns” the mapping between the Control center and the task-specific units involved on that trial by strengthening the

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