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ORIGINAL ARTICLE

Congruency sequence effects and previous response times: conflict adaptation or temporal learning?

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Abstract In the present study, we followed up on a recent report of two experiments in which the congruency sequence effect—the reduction of the congruency effect after incongruent relative to congruent trials in Stroop-like tasks—was observed without feature repetition or contingency learning confounds. Specifically, we further scrutinized these data to determine the plausibility of a temporal learning account as an alternative to the popular conflict adaptation account. To this end, we employed a linear mixed effects model to investigate the role of previous response time in producing the congruency sequence effect, because previous response time is thought to influence temporal learning. Interestingly, slower previous response times were associated with a reduced current-trial congruency effect, but only when the previous trial was congruent. An adapted version of the parallel episodic processing (PEP) model was able to fit these data if it was additionally assumed that attention "wanders" during different parts of the experiment (e.g., due to fatigue or other factors). Consistent with this assumption, the magnitude of the congruency effect was correlated across small blocks of trials. These findings demonstrate that a temporal learning mechanism provides a plausible account of the congruency sequence effect.

Introduction

Performance in distractor interference (i.e., Stroop-like) tasks is typically impaired when there is conflict between distractor and target stimuli. The prototypical example is the Stroop task (Stroop, 1935), wherein participants are usually slower and less accurate to identify the print color of incongruent color words (e.g., the word "red" printed in green) relative to congruent color words (e.g., "red" printed in red). Analogous congruency effects are observed in the Simon (Simon & Rudell, 1967) and Flanker (Eriksen & Eriksen, 1974) tasks.

It is frequently argued that participants adapt to conflict between targets and distractors by directing attention toward the target and/or away from the distractor in the next trial. One of the most common approaches to studying this hypothesized process is to investigate the congruency sequence effect (CSE; Gratton, Coles, & Donchin, 1992). A CSE is observed when the size of the congruency effect in the current trial depends on the congruency of the previous trial. More specifically, a CSE is observed when the congruency effect is smaller following incongruent relative to congruent trials. According to the conflict adaptation account (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001), the CSE occurs because participants increase perceptual attention to the target and/or reduce perceptual attention to the distractor following incongruent trials to avoid re-experiencing conflict.

However, an alternative account suggests that the CSE is due to learning and memory confounds (Schmidt, 2013a; see also, Schmidt, Notebaert, & Van Den Bussche, 2015). For instance, feature repetition confounds, caused by repeating the target and/or distractor from one trial to the next, can engender a CSE in the absence of conflict adaptation (Hommel, Proctor, & Vu, 2004; Mayr, Awh, &

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Laurey, 2001). Similarly, contingency learning confounds, caused by presenting each distractor stimulus with a congruent target more often than with an incongruent target (a common procedure in the literature), can also engender a CSE in the absence of conflict adaptation (Mordkoff, 2012; Schmidt & De Houwer, 2011). An ongoing debate in the literature therefore concerns whether the CSE is solely explained by feature repetition and contingency learning confounds, or whether conflict adaptation also contributes to the CSE (e.g., Schmidt, De Schryver, & Weissman, 2014a; for reviews, see Egner, 2007; Schmidt, 2013a).

In a recent paper (Schmidt & Weissman, 2014; see also, Weissman, Jiang, & Egner, 2014), we showed that feature repetition and contingency learning confounds cannot entirely explain the CSE in the prime-probe task (for related research with other tasks, see Blais, Stefanidi, & Brewer 2014; Duthoo, Abrahamse, Braem, Boehler, & Notebaert, 2014; Jiménez & Méndez, 2012; Kim & Cho, 2014). In each trial, participants were asked to discriminate the direction indicated by a target word (“Left,” “Right,” “Up,” or “Down”) with a spatially compatible key press. Critically, the target (e.g., “Left”) was preceded by an array of three vertically stacked distractor words that indicated the same direction (e.g., “Left,” “Left,” “Left”) or the opposite direction (e.g., “Right,” “Right,” “Right”). To prevent feature repetition confounds, we presented distractor–target combinations made of the words “Left” and/or “Right” in odd trials and distractor–target combinations made of the words “Up” and/or “Down” in even trials. To prevent contingency learning confounds, we presented each distractor (e.g., “Up”) equally often with the congruent target (e.g., “Up”) and with the opposite-direction incongruent target (e.g., “Down”). Unlike in some previous experiments (Mordkoff, 2012; Schmidt & De Houwer, 2011), we observed a CSE after controlling for both types of confounds.

One conclusion researchers may draw is that this CSE provides strong evidence for conflict adaptation. However, such a conclusion is not a necessary inference. Simple learning and memory biases have already been shown to explain a substantial portion of the effect (e.g., Hommel et al., 2004; Mayr et al., 2001) and further such confounds may explain the rest.

One such confound is temporal learning (Schmidt, 2013a, b). In this view, learning is not only about determining what response to make (e.g., based on a contingency or associative mechanism), but also about determining *when* to respond (e.g., based on previous response times). A sequence of notes, for instance, does not make a song without the right timing. Although there are many accounts of how temporal learning emerges (e.g., Grice, 1968; Kohfeld, 1968; Ollman & Billington, 1972), we focus on just one for expositional simplicity. Other accounts, however, would have similar implications for the CSE. Thus, rather than advocating for any particular account, we simply put forward the general claim that temporal learning, more broadly, may have implications for the CSE. As described next, this is because a critical byproduct of temporal learning is rhythmic behavior (Grosjean, Rosenbaum, & Elsinger, 2001).

One way in which rhythmic biases could arise is via the development of learning-derived expectancies about when to respond from one moment to the next. Simply put, learning the trial-by-trial rhythm of a task will lead participants to expect to respond quickly following a quick response, and slowly following a slow response. In the context of a psychological experiment, this could lead response times on trial n to be highly correlated with those on trial $n - 1$, which is already a well-documented finding in the literature (e.g., Kinoshita, Forster, & Mozer, 2008; Kinoshita, Mozer, & Forster, 2011). This is a significant consideration when thinking about the nature of the CSE. Since response times are generally faster in congruent than in incongruent trials, participants should expect to respond more quickly on trial n when trial $n - 1$ was congruent, relative to incongruent.

An example mechanism by which such a temporal expectancy could produce a CSE is presented in Fig. 1, wherein the response threshold drops temporarily at around the time that a participant expects to respond. As will be demonstrated later with a computational model, this can be achieved solely via the retrieval of response time information from previously encountered trials from memory. How does the mechanism work? Following congruent trials, the response threshold drops early in the course of the current trial (i.e., at around the time a response was made in the previous trial). Congruent trials benefit from this reduced threshold, resulting in especially fast responses. In contrast, activation on incongruent trials accrues too slowly to cross the threshold while it is temporarily reduced early in the trial, resulting in no benefit. Thus, the difference in mean RT between incongruent and congruent trials is accentuated following congruent trials, leading to a large congruency effect.

The opposite effect occurs following incongruent trials: the response threshold drops later (rather than earlier) in the current trial (i.e., again, at around the time a response was made in the previous trial). Incongruent trials benefit from this reduced threshold because activation has had sufficient time to build. It is therefore able to cross the reduced threshold, which leads to faster responses. Congruent trials do not benefit, however, because responses in these trials are usually made before the response threshold drops. Thus, the difference in mean RT between incongruent and congruent trials is reduced following incongruent trials, leading to a small congruency effect. As

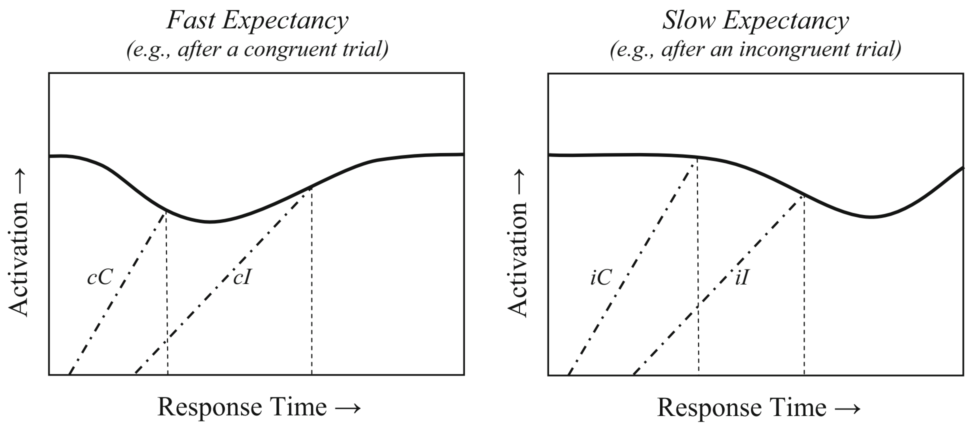

Fig. 1 An example of temporal learning mechanism with a fast (*left*) versus a slow (*right*) temporal expectancy. The *thick solid line* represents the response deadline, and the *dashed dotted lines* represent the accumulation of activation over time for a typical congruent and incongruent trial

described above (see also Fig. 1), a temporal learning mechanism predicts that the congruency effect will be larger following congruent (fast) responses than after incongruent (slow) responses. A CSE could therefore be produced by temporal learning, rather than by conflict adaptation. Put differently, a mechanism that learns exclusively based on previous response times and which is entirely blind to congruency or conflict may be sufficient to explain CSEs in tasks that lack feature repetition and contingency learning confounds. If this is the case, then accounting for the effect of previous RT on the congruency effect should reduce the CSE. In other words, accounting for the effect of previous RT should explain variance in the CSE that reflects learning from previous response times.

It is important to note that the temporal learning account of the CSE is similar to some variants of the attentional adaptation account. For example, it is similar to the original account of Gratton, Coles and Donchin (1992), in which learning and expectancies also influence the CSE (see also, Hazeltine, Akçay, & Mordkoff, 2011; Schmidt & De Houwer, 2011). However, the temporal learning account assumes that response time, rather than congruency and/or conflict, underlies whatever learning and expectancies lead to a CSE. Further, the adjustments of the response threshold that result from learning about when to respond have nothing to do with attentional adjustment at perceptual levels of processing. Thus, while the temporal learning hypothesis shares features with certain variants of the attentional adaptation account, it also differs from those variants in important ways.

As explained above, the temporal learning account predicts a two-way interaction between previous RT and current congruency in experiments investigating the CSE (i.e., the congruency effect should be larger following faster previous RTs). The temporal learning account might also predict a three-way interaction between previous RT, previous congruency, and current congruency. What form might this three-way interaction take? Prior work demonstrates that easier trial types (e.g., congruent trials) are more strongly affected by expectancy-based changes in response threshold than harder trial types (e.g., incongruent trials) in both human participant and computationally modeled data (e.g., see Kinoshita et al., 2011).

Though the reasons for this can be complex, comparing the left and right panels of Fig. 1 can help explain why larger effects might be expected for congruent trials.[1] As shown in the left panel, following a fast (e.g., congruent) response, congruent trials are very likely to benefit from an expectancy for another quick response. In contrast, following a slow (e.g., incongruent) response, congruent trials are very unlikely to benefit from an expectancy for a slow response. A congruent response is likely to be made well before the slow expectancy starts affecting the response threshold (i.e., unless evidence accrual happens to occur particularly slowly on that trial). Thus, whether a congruent trial benefits from a temporal expectancy will be strongly determined by how early that expectancy occurs. Critically, as shown in the right panel, some of these effects are less pronounced for incongruent trials. Following a slow (e.g., incongruent) response, many incongruent trials will benefit from an expectancy for another slow response. However, following a fast (e.g., congruent) trial, some incongruent

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[1] Figure 1 roughly illustrates why the parallel episodic processing model, discussed later, produces a larger effect of expectancy-based changes in the response threshold for congruent relative to incongruent trials. The point at which evidence for a response will begin to increase and the steepness of the slope of increasing activation will vary from trial to trial within both the congruent and incongruent conditions. The evolution of the response threshold over time will also vary from trial to trial depending on the speed of responding in the last few trials. However, the figure demonstrates why, generally, congruent trials are more affected than incongruent trials by expectancies following fast congruent relative to slow incongruent responses. Congruent trials will generally benefit from a fast expectancy, but will “beat” the response threshold dip with a slow expectancy. In contrast, incongruent trials will not only benefit from slow expectancies, but will also often be fast enough to benefit from a fast expectancy.

trials will benefit from an expectancy for a quick (e.g., congruent) response. In particular, there will often be enough evidence to respond early (i.e., when interference is not too overwhelming and evidence accrues quickly enough), particularly given that the response threshold has been reduced. Thus, the effect of expectancy-based changes in the response threshold is somewhat smaller for incongruent than for congruent trials. Given these considerations, a three-way interaction between previous RT, previous congruency, and current congruency might be anticipated in the human participant data from our prior study (Schmidt & Weissman, 2014).

Analysis 1: experimental data

In Analysis 1, we conducted a linear mixed effects (LME) model to determine the effect of previous RT on the size of the congruency effect. As described above, the temporal learning account predicts that the congruency effect should increase as previous-trial RT decreases. This, in turn, should explain some or all of the variance in the CSE. A three-way interaction between previous RT, previous congruency, and current congruency might also be expected, because congruent trials are thought to be more sensitive to changes in the response threshold (e.g., Kinoshita et al., 2011).

Method

We used an LME model, which includes every observation within each participant, to determine the effects of previous RT, previous congruency, and current congruency on current trial RT. Experiments 1 and 2 from Schmidt and Weissman (2014) were combined into one analysis, with experiment included as a random effect (separate analyses on each of the two experiments revealed the same pattern of significant results in each experiment). For this analysis, we did not analyze error rates. A significant CSE was observed in the errors of Experiment 1 and there was a non-significant trend in the same direction in Experiment 2, but the error effects were generally much less robust than the RT data, making it problematic to split the error data further to assess the higher-order interactions involved in the current LME. However, we do return to the error rate CSE in the simulations to follow (Analyses 2 and 3).

Standard data treatments were conducted prior to implementing the LME model. Response times for correct trials that were preceded by correct trials during the main part of the experiment (practice trials excluded) were submitted to the LME regression. Similar to Kinoshita et al. (2011; see also, Schmidt, 2013b; Schmidt, Lemercier, & De Houwer, 2014b), response times were inverse transformed (−1000/RT). This was a necessary step to produce the normal distribution required for LME regression, as response time distributions are heavily skewed. Investigation of the Q–Q plot of inverse response times revealed the need to trim response times that were less than 300 ms on the current and previous trial to further normalize the response time distribution (75 observations, approximately 0.3 % of the data). Previous response times were centered on the grand mean to avoid correlation with the intercept. Analyses were run using the MIXED procedure in SPSS with congruency, previous congruency, and previous RT as fixed factors, and subjects and experiment as random factors.

Results

Main effects

The results of the previous RT × previous congruency × current congruency LME regression are presented in Table 1, including the model parameters and statistical tests. Because of the inverse transform, the parameters are inevitably difficult to interpret on their own, but the meaning of each test will be described below. There were three significant main effects. First, a main effect of current congruency was observed, indicating faster responses in congruent relative to incongruent trials. Second, there was a main effect of previous congruency, indicating faster responses following incongruent relative to congruent trials. Third, there was a main effect of previous RT, indicating that response times on the current trial varied positively with response times on the previous trial.

Two-way interactions

There were three significant two-way interactions. First, there was an interaction between previous congruency and current congruency, indicating a CSE independent of previous RT. Second, previous RT interacted with current congruency, indicating that the slower the previous RT, the smaller was the congruency effect on the current trial. As described in “Introduction”, this interaction is predicted by the temporal learning account. Third, previous RT interacted with previous congruency, indicating that the relationship between current RT and previous RT was more positive after congruent trials, relative to incongruent trials. We discuss a potential explanation for this interaction in Analysis 3.

Three-way interaction

The three-way interaction among previous RT, previous congruency, and current congruency was significant,

Table 1 Analysis 1: linear mixed effects model coefficients and statistics for congruency × previous congruency × previous RT on inverse RT

Variable	Estimate	SE	*t*	*p*
Congruency	0.332724	0.006585	50.531	<0.001
prevCon	−0.034202	0.006742	−5.073	<0.001
prevRT	0.286248	0.009932	28.822	<0.001
Congruency: prevCon	−0.054259	0.009355	−5.800	<0.001
Congruency: prevRT	−0.148572	0.013225	−11.234	<0.001
PrevCon: prevRT	−0.032678	0.014996	−2.179	0.029
Congruency: prevCon: prevRT	0.130459	0.021009	6.210	<0.001

prevCon previous congruency, *prevRT* previous response time

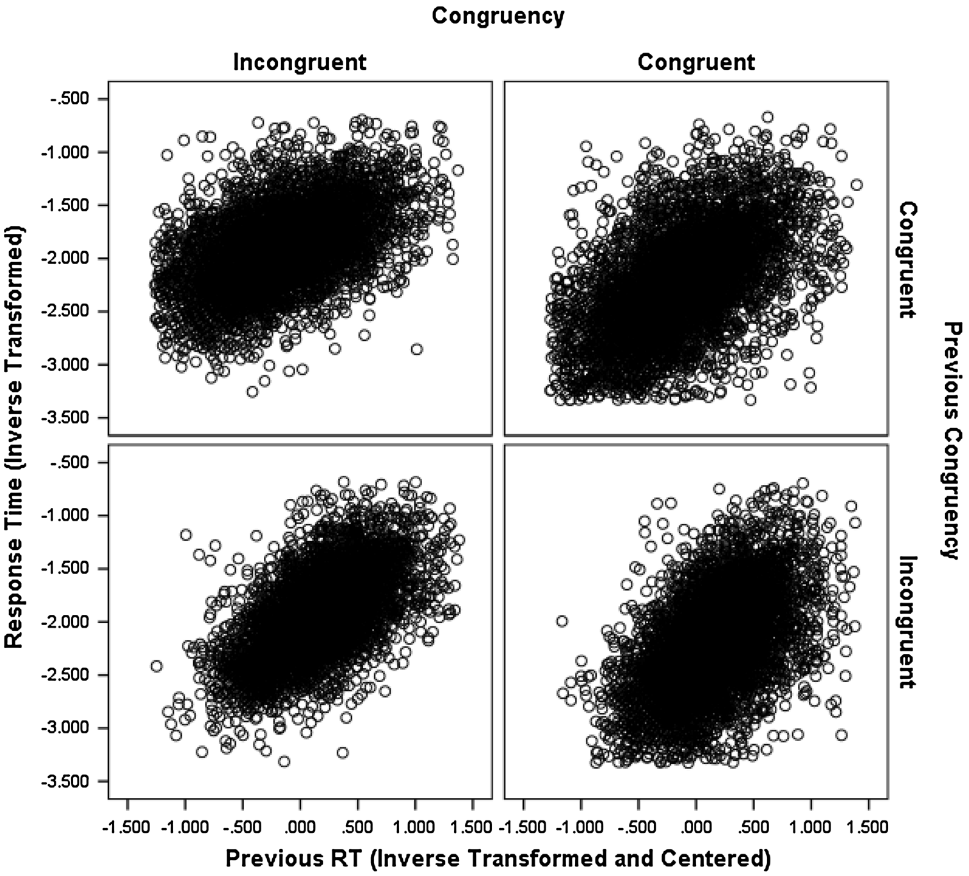

Fig. 2 The correlation between previous and current RT, separated by previous and current congruency

indicating that the relationship between previous RT and current congruency was larger following congruent relative to incongruent trials. This can be seen graphically in the scatter plots presented in Fig. 2. Separate tests of the slopes for the previous RT by current congruency interaction following congruent and incongruent trials revealed that the interaction was significant following congruent trials (estimate: −0.140649; SE: 0.015067), $t(10679) = -9.335$, $p < 0.001$, but not following incongruent trials (estimate: −0.017756; SE: 0.017819), $t(10967) = -0.966$, $p = 0.319$. Thus, the congruency effect was only modified (significantly) by previous RT following congruent trials.

Discussion

Consistent with the temporal learning account, the congruency effect varied with previous RT. More specifically, the congruency effect decreased as previous RT increased. This interaction explains variance in the CSE, because previous RT and previous congruency are correlated (i.e., congruent trials tend to be faster than incongruent trials). Indeed, the parameter for the CSE (previous congruency × congruency) was −0.077895 without previous RT in the model, and only −0.054259 with previous RT in the model. However, the CSE was still significant after controlling for previous RT, indicating that previous response times are not the whole story.

Also important, there was a three-way interaction between previous RT, previous congruency, and current congruency. This interaction occurred because the current-trial congruency effect was smaller after slow relative to fast congruent trials, but roughly equivalent in size after slow relative to fast incongruent trials. As previously discussed, the temporal learning account predicts this sort of three-way interaction, because congruent trials are anticipated to be more sensitive to expectancy-based changes in the response threshold. Thus, these initial findings seem consistent with the temporal learning view. Nonetheless, whether the temporal learning account can explain the full pattern of data is not immediately apparent. To investigate this issue, we employed computational modeling.

Analysis 2: temporal learning

The goal of Analysis 2 was to determine whether or not the temporal learning mechanism described in "Introduction" produces effects that are consistent with the LME results from Analysis 1. We therefore used the parallel episodic processing (PEP) model of Schmidt (2013c) to simulate the experiments reported in Analysis 1. Specifically, we used a variant of the PEP model that has already been adapted to learn about time for other purposes (Schmidt, 2013b). To determine whether the model produced data that were compatible with the experimental data, an LME model on the simulated data was performed exactly as described in Analysis 1.

Methods

Basic model overview

The PEP model is visually represented in Fig. 3. A full description of the model parameters can be found in Schmidt (2013c). Source code for this version of the model (and for all previous versions) can be found on the lead author's website (http://users.ugent.be/~jaschmid/PEP). Note that some minor changes were made to the model in this and the following simulation, but the model still produces item-specific (Schmidt, 2013c) and list-level proportion congruent effects (Schmidt, 2013b). Thus, any changes to the model mentioned below do not undermine the ability of the model to explain phenomena that it was previously reported to simulate. Although all changes made to the model are noted below, the only meaningful change worth noting is that the temporal learning mechanism (described below) was made to be more strongly influenced by recent responses and less by older ones. This is an important change for allowing the response speed of the immediately preceding trial to have a noticeable impact on behavior.

The model operates as follows. Input nodes for targets and distractors are stimulated first. Input nodes then stimulate Identity nodes, where conflict can occur. Identity nodes then stimulate Response nodes. Input nodes for distractors also activate the Episode nodes (each

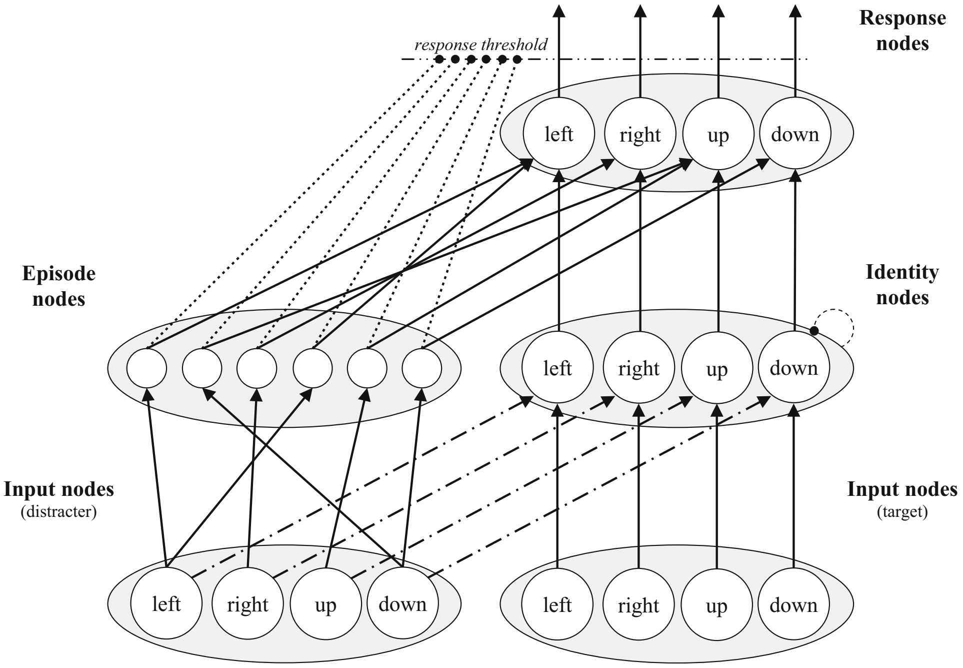

Fig. 3 A representation of the parallel episodic processing (PEP) model

corresponding to one previously experienced trial) with which they are connected. Though not relevant for the contingency-unbiased task modeled here, Episode nodes then bias the Response nodes with which they are connected, producing contingency learning.

The key addition of Schmidt (2013b) that is most relevant for the current work is that, in addition to storing the links between stimuli and responses, each Episode also stores the response time for the corresponding trial. These stored response times are retrieved on subsequent trials and bias the global response threshold of the Response nodes. That is, the model uses memories of previous response times to expect when to respond. Specifically, the response threshold is reduced most when the cycle time is close to recently stored response times (see Fig. 1). Thus, the model is biased to respond at a similar speed as in recent trials. Note that the model only stores information about response times. The dips in the response threshold (i.e., temporal expectancies) are recomputed from a new memory search on each trial. The exact mechanism by which this is achieved is explained in the following section.

Temporal learning mechanism

The final cycle time (i.e., simulated RT) of a trial was recorded into each Episode node on each trial. On subsequent trials, this RT information was used to decrease the response threshold as the cycle approached the stored RT. This threshold biasing was strongest for the most recently encoded Episode nodes. The response threshold was set dynamically on each processing cycle using the formula,

$$\text{Threshold} = \text{baseline} - \left(\sum_{i=1}^{n}(\text{proximity}_i \times \text{strength}_i) - 0.05\right). \tag{1}$$

The threshold value was restricted between 0.30 (maximum decrease) and 0.45 (the baseline threshold), and the threshold only dropped after a retrieval bias of 0.05 (increased from 0.01). Proximity was calculated as

$$\text{Proximity}_i = 1 - \left(\frac{(\text{cycle} - \text{rt}_\text{i})^2}{10{,}000}\right). \tag{2}$$

The proximity of each episode *i* was restricted between 0 and 1. This formula produces a value of 1 when the current cycle time (cycle) and the stored cycle time of the episode (rt) are identical, and decreases to a value of 0 if rt and cycle differ by more than ±100 cycles. The strength of episode *i* is determined by the formula,

$$\text{Strength}_i = \frac{(6 - \text{lag}_\text{i})^3}{500}. \tag{3}$$

This formula is only applied to the most recent five Episodes (down from 40), and lag represents how many trials previously a given Episode *i* occurred. The most recent trial can have a strength value as high as 0.25, and this decreases logarithmically as lag increases. In other words, the most recent trial has a large impact, whereas older trials have a much reduced impact. In the previous version, the formula was the square of $(40 - \text{lag}_i)$ divided by 50,000. Thus, the newer version puts more emphasis on the most recent trials and less on older ones. This weighting of past trials is of importance in producing a CSE, because the effect of the immediately preceding trial was diluted in the previous version of the model. However, this new version not only “works” better for the current purposes, but also appears more consistent with (unreported) analyses of participant data that take into account multiple previous response times. This change also reduces the processing demands of the model substantially.

Minor model changes

Note that the model also incorporates the minor parameter changes made in Schmidt (2013b). In addition to being reverse compatible with the original results of Schmidt (2013c), these minor changes are not critical for the simulations reported here and served merely to produce a more realistic response time distribution. The only novel change in the current instantiation is that the normal distribution of bias scores (noise for Input nodes) averaged four rather than three random numbers, which again did nothing more than produce a more realistic response time distribution. To substantially improve simulation times, Episode nodes receiving no input and with an activation level of less than 0.0001 were no longer updated. Nodes meeting these conditions were no longer retrievable anyway, and the new change speeds simulation times by roughly an order of magnitude.

Materials and design

The model was presented with the same manipulations as those in Schmidt and Weissman (2014). Specifically, distractors were presented for 133 cycles prior to offset, followed by a 33 cycle “blank screen,” and then the target for 133 cycles. We assumed that activation of the stimuli would be reduced only slightly at offset, but that activation would be decreased substantially for the distractor when it was masked by the target. These effects, respectively, were modeled as a 2 % reduction of the signal and bias values that influence the input to the node on offset and by the elimination of the signal from the distractor when it was masked by the target. Adjustment of these parameters within reasonable margins does not have a sizeable effect on the results.

As in the experiment with human participants, there were eight 96-trial blocks. Left and right distractors were presented equally often with left and right targets on odd trials, and up and down distractors were presented equally often with up and down targets on even trials. Trials were congruent if the distractor and target matched (e.g., left and left) and incongruent if they mismatched (e.g., up and down). This design prevented feature repetitions in consecutive trials. It also prevented contingency learning biases from being confounded with the CSE, because it paired each distractor equally often with one congruent target and one incongruent target (e.g., the left distractor was presented equally often with the left and right targets). Finally, it ensured an equal number of trials in each of the four cells of the previous congruency (congruent, incongruent) × current congruency (congruent, incongruent) design. Previous RT, previous congruency, and current congruency were coded for each trial, and an LME regression was performed identically to the one described in Analysis 1, including data treatments, with the exception that inspection of the Q–Q plots revealed no need for trimming responses faster than 300 ms.

Results

Though not reported for brevity, several runs with differing parameters were conducted (e.g., while the new mechanisms were being added and bug fixed, or merely to see whether certain parameters affected the outcome in any notable way). The simulation results reported below were consistently observed when reasonable adjustments of the parameters in the PEP model were made, with two exceptions noted below.

Traditional analysis

Before proceeding to the LME results, we first report the results of the model using the standard analysis with untransformed RTs and not including the previous RT factor. In this analysis, the PEP model produced a CSE in both the response times (effect 6 cycles), $F(1,999) = 32.023$, $\mathrm{MSE} = 264$, $p < 0.001$, and the error rates (effect: 0.34 %), $F(1,999) = 82.045$, $\mathrm{MSE} = 0.357$, $p < 0.001$.

Main effects

The results of the previous RT × previous congruency × current congruency LME regression are presented in Table 2, including the model parameters and statistical tests. Many of the results paralleled the participant data in Analysis 1. First, a significant congruency effect was observed, indicating faster responses in congruent relative to incongruent trials. Second, the main effect of previous RT was also significant, indicating that response times on the current trial varied positively with response times on the previous trial. Third, the main effect of previous congruency was significant, but less robust than some of the other observed effects to changes in model parameters.

Two-way interactions

First, previous RT interacted with current congruency, indicating that the slower the previous RT, the smaller was the congruency effect on the current trial. As noted earlier, this is the key prediction of the temporal learning account. Second, while a CSE was produced by the PEP model with the traditional analysis (i.e., using untransformed RTs and not taking into consideration previous RT), and also in an (unreported) LME that did not include previous RT, the interaction between previous congruency and current congruency was not significant in the current LME. This result indicates that the model produces a CSE that is almost entirely explained by previous RT. However, whether or not the interaction between previous congruency and current congruency was observed (i.e., independent of the previous RT bias) was highly parameter dependent, much like the main effect of previous congruency. We discuss this in greater detail later. Third, previous RT interacted with previous congruency. However, the form of this interaction was opposite to that in the human participant data: the relationship between current RT and previous RT was more positive after incongruent trials than after congruent trials. We discuss a potential explanation for this result in Analysis 3.

Three-way interaction

Consistent with Analysis 1, the three-way interaction among previous congruency, previous RT, and congruency was significant: the relationship between previous RT and current congruency was larger after congruent relative to incongruent trials.

Discussion

The simulation results replicated most of the key findings from Analysis 1. First, the LME model revealed that the current-trial congruency effect decreased as previous RT increased. Second, a CSE was produced by the PEP. However, unlike in the human participant data, previous RT explained most of the CSE. That is, the previous congruency by current congruency interaction was no longer significant after adding previous RT to the model. The lack of a CSE independent of previous RT may indicate that the

Table 2 Analysis 2: linear mixed effects model coefficients and statistics for congruency × previous congruency × previous RT on inverse RT

Variable	Estimate	SE	*t*	*p*
Congruency	0.403595	0.002738	147.431	<0.001
prevCon	−0.029271	0.002746	−10.658	<0.001
prevRT	0.232377	0.002104	110.421	<0.001
Congruency: prevCon	0.004030	0.003893	1.035	0.301
Congruency: prevRT	−0.128511	0.002977	−43.163	<0.001
prevCon: prevRT	0.050426	0.003202	15.748	<0.001
Congruency: prevCon: prevRT	0.022079	0.004534	4.869	<0.001

prevCon previous congruency, *prevRT* previous response time

PEP model needs to be adjusted with better parameters. Alternatively, it might suggest that previous congruency plays a role in producing the CSE independent of previous RT, consistent with the data of Weissman and Carp (2013). We return to this point in the "General discussion".

Interestingly, the model did produce the expected three-way interaction between previous RT, previous congruency, and current congruency. Consistent with previous work by Kinoshita et al. (2011), previous RT had a larger influence on the current-trial congruency effect when the previous trial was congruent relative to incongruent. The PEP model did not, however, completely replicate the entire pattern of human participant data. For instance, the direction of the previous congruency by previous RT interaction was opposite to that observed in the human participant data. Such inconsistencies may appear to suggest that the temporal learning account of the CSE is incorrect. However, it is also possible that the temporal learning account is correct and that a different mechanism unrelated to the CSE explains the remaining inconsistencies. The next section explores one such possible mechanism.

Analysis 3: attentional wandering

The goal of Analysis 3 was to addresses a shortcoming of our previous analyses. Note that in human participant data, there are many sources of error in measurement. For instance, there can be intra-individual differences in response time or variance in response time (Jensen, 1992), periods of attentional lapses (Smallwood & Schooler, 2006) or fatigue (Boksem, Meijman, & Lorist, 2005), and other factors that impact the distribution of the data. Often such factors are not simulated in a computational model, which is not a problem if such factors have no qualitative impact on the effect being modeled. As we will illustrate shortly, however, in some scenarios unmodeled error does have a qualitative impact.

Of particular interest for the current discussion, the computational model in Analysis 2 provided no means by which the size of the congruency effect could vary over time. There is, of course, some error in the PEP model. To produce a realistic response time distribution (and also some errors), there needs to be some error in the inputs to the nodes (e.g., sometimes the distracting stimulus will accrue evidence particularly quickly, and at other times more slowly). However, in the simulation just presented, this random noise was not correlated from one trial to the next. For instance, a more strongly activated distractor on Trial $n - 1$ had no implications for whether or not the distractor would again be strongly activated on the following trial.

More realistically, participants' attention to the task will vary across time (e.g., Boksem et al., 2005; Smallwood, McSpadden, Luus, & Schooler, 2008). Thus, there will be some periods during which the distractor has a particularly large impact on a participant's performance, and others during which it has less of an impact. During the former periods, relatively large congruency effects will be observed on both the previous and current trial. During the latter periods, relatively small congruency effects will be observed. More broadly, as mentioned above, attention to each of the stimulus dimensions likely varies across time due to factors such as motivation and fatigue (e.g., Boksem et al., 2005) or mind wandering (for a review, see Smallwood & Schooler, 2006). As long as this variation of attention occurs gradually (or, more specifically, tends to correlate from one trial to the next), large congruency effects will tend to be followed by large congruency effects, and small by small (as explained earlier). We call this view the attentional wandering hypothesis.

Attentional wandering does not produce a CSE, as we will demonstrate later, but does have major implications for some of the interactions involving the previous RT factor. The consequences of such wandering are shown in Table 3. Consider trials wherein distractor attention is relatively high. Response times on congruent trials will be faster than usual (increased facilitation), while response times on incongruent trials will be slower than usual (increased interference). Since attention wanders gradually, congruency effects will be large after (a) congruent trials

Table 3 Example of attentional wandering account

Previous congruency	Previous RT	Distractor attention	Current congruency	Current RT
Incongruent	↑	High	Incongruent	↑
			Congruent	↓
	↓	Low	Incongruent	↓
			Congruent	↑
Congruent	↑	Low	Incongruent	↓
			Congruent	↑
	↓	High	Incongruent	↑
			Congruent	↓

↑ = longer (slower) RT, ↓ = shorter (faster) RT

with relatively fast response times and (b) incongruent trials with relatively slow response times. Now, consider trials in which attention to the distractor is relatively low. Response times on congruent trials will be slower than usual (decreased facilitation), while response times on incongruent trials will be faster than usual (decreased interference). Congruency effects will therefore be small after (a) congruent trials with relatively slow response times and (b) incongruent trials with relatively fast response times.

In sum, larger current-trial congruency effects should be associated with faster previous congruent RTs and with slower previous incongruent RTs. Thus, periods of attentional wandering should contribute to the three-way interaction among previous congruency, previous RT, and current congruency that we observed in the human participant data. It is important to reiterate that the attentional wandering mechanism simply makes the congruency effect at a given point in the experiment somewhat correlated with the magnitude of congruency effects in recent trials. While this assumption appears reasonable, we directly test it in Analysis 4.

Given the considerations above, we investigated whether combining the temporal learning and attentional wandering mechanisms might provide a more complete account of the human participant data than the temporal learning mechanism alone. Notably, a model that combines these mechanisms should still produce a three-way interaction among previous congruency, previous RT, and current congruency. After congruent trials, both temporal learning and attentional wandering should produce smaller congruency effects after relatively slow response times than after relatively fast response times. Following incongruent trials, however, the situation is more complex. While the temporal learning mechanism should produce smaller congruency effects after relatively slow response times than after relatively fast response times, the attentional wandering mechanism should produce the opposite pattern. Thus, the two mechanisms should tend to counteract each other. This property should lead to a three-way interaction among previous congruency, previous RT, and current congruency. It may also explain why, in the human participant data, previous RT influenced the current-trial congruency effect after congruent trials, but not after incongruent trials.

A combination of temporal learning and attentional wandering mechanisms should also produce a two-way interaction between previous congruency and previous RT of the correct form (i.e., an interaction wherein previous RT is more predictive of current RT when the previous trial is congruent, relative to incongruent). To understand why, first consider that a relatively quick response in an incongruent trial could arise via: (1) a temporal expectation to make a fast response or (2) a reduction of attention to the distractor. In the former case, response time should be facilitated more in a subsequent congruent trial than in a subsequent incongruent trial, because congruent trials are more likely to benefit from an expectancy to respond quickly than incongruent trials. In the latter case, response time should be facilitated more in a subsequent incongruent trial than in a subsequent congruent trial, because a reduction of attention to the distractor should both reduce interference in an incongruent trial (thereby speeding RT) and reduce facilitation in a congruent trial (thereby slowing RT). Thus, a relatively quick response in a previous incongruent trial should not be strongly predictive of current RT, because response speed in the current trial depends on why the previous incongruent trial RT was faster than usual.

Next, consider that a relatively quick response in a congruent trial could arise from (1) a temporal expectation to make a fast response or (2) an increase of attention to the distractor. Both of these mechanisms should facilitate response time more in a subsequent congruent trial than in a subsequent incongruent trial. Thus, a relatively quick response in a previous congruent trial should be strongly predictive of current response time, because response speed in the current trial should not depend on why the previous congruent trial RT was faster than usual. In short, combining the temporal learning and attentional wandering mechanisms should lead to a stronger relationship between previous RT and current RT when the previous trial was congruent as compared to incongruent. Thus, a model that combines these mechanisms could produce an interaction between previous congruency and previous RT of the correct form.

Perhaps the attentional wandering hypothesis lacks a certain level of intuitive appeal because it suggests somewhat complex relationships among previous congruency, previous RT, and current congruency. The only assumption the account makes, however, is that attention to the distractor varies gradually over time, which appears reasonable (e.g., Boksem et al., 2005; Smallwood et al., 2008). Further, the complex predictions of this account are merely the logical by-products of this assumption. Indeed, even the exact mechanism and the way we program it in the model are not so crucial: as long as we assume (for one reason or another) that the size of the congruency effect varies gradually over time and correlates from one trial to the next, the same conclusions follow. The current simulation simply aims to add a more realistic "structure" to the random error in the model. We therefore investigated whether combining the temporal learning and attentional wandering mechanisms within a single model could better account for the human participant data.

Methods

Key model changes

The PEP model from Analysis 2 was adapted such that the signal strength (i.e., the input activation of a presented stimulus) of activated distractor Input nodes was increased or decreased randomly from trial to trial. The signal value was increased or decreased by a small amount on each trial, and how much the signal changed in a given direction on a given trial was partly determined by the increase or decrease on the previous trial. Specifically, the signal for the presented distractor on a given trial was determined with the formula

$$\begin{aligned}\text{Signal}_n = {} & \text{signal}_{n-1}(0.9) + \text{signal}_{base}(0.1) \\ & + \text{deflection}_n.\end{aligned} \tag{4}$$

The signal of a given trial n is thus highly similar to that of the previous trial ($n - 1$), but is regressed partially toward the normal (base) signal of 0.9 (i.e., to prevent a runaway increase or decrease). The signal is able to deviate from the base value with the deflection parameter, calculated with the formula,

$$\text{Deflection}_n = \text{deflection}_{n-1}(0.95) + \text{random}_n(0.05). \tag{5}$$

The deflection on a given trial n is thus highly similar to the deflection on the previous ($n - 1$) trial and is adjusted by the random parameter added on each trial (a random normal number between -1 and $+1$ created by subtracting one random number from another). The deflection parameter thus works to occasionally gradually increase or decrease for a string of trials, but has the tendency to regress back to a baseline value of 0 over time, a bit similar to Formula 4. The net result of the two formulas is that the signal value will tend to hover around 0.9 with the occasional string of trials with either increased or decreased values, simulating periods of high and low distractor attention, respectively.

Design

The design was identical in all respects to Analysis 2. The only difference between Analyses 2 and 3 was the change to the PEP framework mentioned above, which involved adding an attentional wandering mechanism.

Results

The modeling results were tolerant of reasonable changes in model parameters and to a greater extent than in the previous simulation.

Traditional analysis

Before proceeding to the LME results, we first report the results of the model using the standard analysis with untransformed RTs and not including the previous RT factor. In this analysis, the PEP model produced a CSE in both the response times (effect: 11 cycles), $F(1,999) = 107.751$, $\text{MSE} = 264$, $p < 0.001$, and the error rates (effect: 0.79 %), $F(1,999) = 278.074$, $\text{MSE} = 0.056$, $p < 0.001$.

Main effects

The results of the previous RT × previous congruency × current congruency LME regression on the PEP data are presented in Table 4, including the model parameters and statistical tests. Critically, the pattern of statistically significant results was identical to the participant data from Analysis 1. First, there was a main effect of current congruency, indicating faster responses on congruent relative to incongruent trials. Second, there was a main effect of previous congruency, indicating faster responses following incongruent relative to congruent trials. Third, there was a main effect of previous RT, indicating that response times on the current trial were correlated with response times on the previous trial.

Table 4 Analysis 3: linear mixed effects model coefficients and statistics for congruency × previous congruency × previous RT on inverse RT

Variable	Estimate	SE	t	p
Congruency	0.425058	0.002795	152.082	<0.001
prevCon	−0.027601	0.002809	−9.826	<0.001
prevRT	0.319882	0.002042	156.654	<0.001
Congruency: prevCon	−0.007196	0.003988	−1.804	0.071
Congruency: prevRT	−0.238294	0.002905	−82.038	<0.001
prevCon: prevRT	−0.050388	0.003205	−15.721	<0.001
Congruency: prevCon: prevRT	0.144088	0.004554	31.642	<0.001

prevCon previous congruency, *prevRT* previous response time

Two-way interactions

As in the human participant data, there were three two-way interactions. First, there was a marginal interaction between previous congruency and current congruency, indicating a CSE. This effect was again sensitive to parameter changes, but less so than in Analysis 2. Second, previous RT interacted with current congruency, indicating that the slower the previous RT, the smaller was the congruency effect on the current trial. Though excluded for brevity, a CSE was absent if the temporal learning mechanism was lesioned, leaving only the attentional wandering mechanism. In contrast, a CSE was present when only the temporal learning mechanism was included in the model (Analysis 2). These results indicate that the temporal learning mechanism, rather than the attentional wandering mechanism, is what produces the CSE in the combined model. Third, as in the human participant data in Analysis 1 (but unlike in the simulated data in Analysis 2), previous RT interacted with previous congruency, because the relationship between previous RT and current RT was more positive after congruent relative to incongruent trials. In short, while the attentional wandering mechanism did not produce a CSE, it helped to produce other patterns observed in the human participant data.

Three-way interaction

The three-way interaction among previous RT, previous congruency, and current congruency was significant, indicating that the relationship between previous RT and current congruency was larger following congruent relative to incongruent trials. Separate tests of the slopes for the previous RT by current congruency interaction following congruent and incongruent trials revealed that the interaction between previous RT and current congruency was significant following both congruent trials (estimate: −0.238294; SE: 0.003073), $t(377375) = -77.542$, $p < 0.001$, and incongruent trials (estimate: −0.094205; SE: 0.003289), $t(373184) = -28.645$, $p < 0.001$, even though it was of smaller magnitude in the latter case. It should be noted that with 1000 simulated participants, these tests had exceptionally high power. Thus, the difference between the significant effect following incongruent trials in the simulated data relative to the nonsignificant effect with 32 human participants should probably not be interpreted too strongly, especially since the effect trended in the same direction in the participant data. The important point is that the current-trial congruency effect was modulated more strongly by previous RT when the previous trial was congruent, relative to incongruent, just like it was in the human participant data.

Discussion

The results of Analysis 3 provided a better fit to the human participant data considered in Analysis 1 than did the results of Analysis 2. Indeed, while the temporal learning mechanism in Analysis 2 failed to perfectly replicate the pattern of significant results observed in Analysis 1, the addition of an attentional wandering mechanism in Analysis 3 led the model to replicate the key findings from Analysis 1. In fact, Analysis 3 yielded the same pattern of significant results as Analysis 1, with the single exception of an additional effect of previous RT on current congruency following incongruent trials. As mentioned previously, this result likely indicates greater power of the 1000-participant simulated sample than for the 32-participant human sample (which yielded a trend in the same direction). These results suggest that a temporal learning account provides a plausible explanation for the significant CSEs observed by Schmidt and Weissman (2014), as long as it is assumed that the congruency effect is of similar magnitude from one trial to the next (e.g., due to attentional wandering, fatigue, or other factors).

Analysis 4: attentional wandering and participant data

Analysis 3 showed that a simulated temporal learning mechanism fits the human participant data when an additional attentional wandering mechanism leads the congruency effect to be correlated across trials. This result adds credence to the notion that temporal learning might explain the CSE in our task if we assume that the congruency effect at one point in time is correlated with the congruency effect at the next point in time. While this assumption appears reasonable, in Analysis 4 we directly tested its validity. In particular, we reanalyzed the human participant data of Schmidt and Weissman (2014) to determine whether the congruency effect is, in fact, correlated across trials.

To conduct this analysis, we split the data from each block into smaller (i.e., "mini") blocks of trials and computed the congruency effect for each mini-block. We then tested whether the congruency effect was correlated across mini-blocks within each participant. Specifically, we tested whether the size of the congruency effect in each mini-block predicts the size of the congruency effect in the next mini-block. We reasoned that such an effect would justify our assumption that the congruency effect is correlated across time. It would also show that the model makes at least one novel prediction that can be verified in human participants.

Method

In Analysis 4, we divided each 96-trial block of Schmidt and Weissman (2014) into four mini-blocks of 24 trials (mini-block duration: 48 s). We reasoned that mini-blocks of 24 trials would provide sufficient temporal resolution for detecting transient changes in the congruency effect across time. Moreover, we reasoned that such mini-blocks would provide a sufficient number of observations per cell (e.g., there was only one empty cell for one participant with this analysis).

Dividing 8 blocks of 96 trials in this manner produced 32 mini-blocks. The first mini-block of each larger block was excluded from subsequent analysis because it was not preceded by a mini-block (i.e., because there was a pause between blocks). Thus, each participant had 24 estimates of the current block congruency effect (dependent variable), each of which was associated with an estimate of the previous block congruency effect (predictor variable). Using these estimates, we employed a linear mixed effect model to test whether the size of the congruency effect in the previous mini-block predicted the size of the congruency effect in the current mini-block. The intercept for each participant was added as a random effect into the model to control for between-participant differences in the overall size of the congruency effect.

Results

As predicted, an LME regression revealed that the size of the congruency effect in the previous mini-block was positively related to the size of the congruency effect in the current mini-block (estimate: 0.103321; standard error: 0.035751), $t(765) = 2.890$, $p = 0.004$. Supplementary analyses revealed that the size of this relationship did not differ between Experiments 1 and 2 of Schmidt & Weissman (2014), $F(1,763) = 0.348$, $p = 0.555$. The effect was also still present, and of comparable magnitude, after controlling for mean mini-block RT (estimate: 0.112647; standard error: 0.035981), $t(764) = 3.131$, $p = 0.002$.

Discussion

The results of Analysis 4 justify our addition of the attentional wandering mechanism to the PEP model in Analysis 3. Indeed, consistent with the operation of such a mechanism, the size of the congruency effect in each 24-trial mini-block of human participant data predicted the size of the congruency effect in the next mini-block. This result justifies our use of this mechanism to explain the interactions involving previous RT that we observed in the preceding analyses. It also confirms that a novel prediction of the PEP model can be verified in human participant data.

It is important to reiterate that while the attentional wandering mechanism explains interactions involving previous RT, it does not explain the CSE. For this reason, neither the exact mechanism that leads the congruency effect to be correlated across time nor the exact manner in which we model this mechanism is crucial. Put differently, as long as we assume (for one reason or another) that the congruency effect varies gradually over time, such that its magnitude correlates across trials, the current instantiation of the PEP model will fit the human participant data. Thus, our finding in Analysis 4 that the size of the congruency effect is correlated across time further demonstrates the viability of a temporal learning mechanism for explaining the CSE.

General discussion

The current paper extends the work we presented in Schmidt and Weissman (2014). In that paper, we observed a CSE in a prime-probe task, wherein we were able to rule out feature integration and contingency learning confounds by design. Although there may be a bias to interpret this finding as strong evidence for conflict adaptation, the present results suggest that it may be due, in whole or in part, to temporal learning.

Temporal learning

A key finding of the present study was that previous response times were related to current-trial congruency effects in the human participant data (Analysis 1). Specifically, slower previous RT was associated with smaller congruency effects on the current trial. This finding is consistent with the temporal learning account. Interestingly, this result was observed only when the previous trial was congruent. Following incongruent trials, there was no (significant) relationship between previous RT and the current-trial congruency effect, resulting in a three-way interaction among current congruency, previous congruency, and previous RT.

Analysis 2 further demonstrated that a simple modeled version of the temporal learning account produced not only a two-way interaction between previous RT and current congruency, but also a three-way interaction among previous RT, previous congruency, and current congruency. Thus, the model mirrored many of the important effects in the human participant data. However, the initial model did fail to explain some of these data. For example, Analysis 2 produced a previous congruency by previous RT interaction of the wrong form. Further, the CSE was almost entirely explained by previous RT in the modeled data, which was not the case in the human participant data. A simple temporal learning mechanism on its own therefore appeared insufficient to account for all of the data. However, as discussed in the following section, this initial simulation employed a model that did not allow for gradual changes in the magnitude of the congruency effect over time.

Temporal learning plus attentional wandering

A problem with the first instantiation of the PEP model in Analysis 2 was that the model provided for no variance in the size of the congruency effect across the duration of the task. This is obviously unrealistic, as Analysis 4 demonstrated. Indeed, each participant's ability to focus on the target, rather than on the distractor, will likely vary gradually over time, as a result of factors like fatigue, distraction, or motivation (Boksem et al., 2005; Smallwood et al., 2008). Analysis 3 therefore explored the possibility that the temporal learning model might better fit the human participant data if such variation in the congruency effect over time was assumed. In particular, we assumed that variability in the size of the congruency effect might be explained by an "attentional wandering" mechanism.

As described earlier, this mechanism assumes that attention to the distractor varies gradually over the course of the experiment, leading to relatively large congruency effects when distractor attention is high and to relatively small congruency effects when distractor attention is low. Critically, adding this mechanism to the model did help to explain the remaining interactions in the data, even though it did not explain the CSE. That is, the attentional wandering mechanism itself did not produce a CSE and is not an account of the CSE per se. However, when combined with the temporal learning mechanism in Analysis 3, the overall pattern of human participant data was reproduced. This result demonstrates that the temporal learning account can provide a good fit to the human participant data as long as it is assumed that the magnitude of the congruency effect varies over the course of the experiment. Analysis 4 validated this assumption by demonstrating that the size of the congruency effect was correlated across successive 24-trial "mini-blocks" of the human participant data. Thus, the temporal learning account provides a viable explanation of the CSEs observed by Schmidt & Weissman (2014).

Conflict adaptation

While the present work indicates the plausibility of a temporal learning account of the CSE in the prime-probe task, it does not inherently rule out the conflict adaptation account as a viable alternative. In the following section, we discuss how different variants of the conflict adaptation account may or may not be able to explain the present findings.

To begin, the conflict adaptation account may be able to explain the relationship we observed between previous-trial RT and the size of the congruency effect. Yeung, Cohen, and Botvinick (2011) suggested that response conflict varies on a trial-by-trial basis with RT within both the congruent and incongruent conditions. More specifically, they argued that conflict is greater in trials with relatively long RTs than in trials with relatively short RTs, even within the congruent condition. Although it may initially seem surprising to talk about response conflict in congruent trials (Grinband et al., 2011), it could arise in various ways (Abrahamse & Braem, 2015; Desender, Van Opstal, & Van den Bussche, 2014; e.g., participants might prepare the wrong response prior to stimulus onset, which conflicts with the correct response that must ultimately be executed). Yeung and colleagues further suggested that RT is a rough estimate of experienced response conflict. Thus, analogous to the temporal learning account, this version of the conflict adaptation account might predict an interaction between previous RT and current congruency (i.e., because variations in previous RT are due to variations in conflict). More specifically, a slow response in the previous trial (indexing heightened conflict) should be followed by a smaller congruency effect in the current trial, whereas a fast response in the previous trial (indexing reduced conflict) should be followed by a larger congruency effect.

However, although the above-mentioned variant of the conflict adaptation account might be construed to predict a relationship between previous RT and the congruency effect, it is less clear whether it would predict some of our other findings. For instance, if previous RT is a measure of previous-trial conflict independent of previous-trial congruency, then one might suppose previous RT should be equally related to the size of the congruency effect following congruent and incongruent trials. That is, one might suppose there should be no interaction between previous RT, previous congruency, and current congruency. Instead, we observed that previous RT is only related to the size of the congruency effect following congruent trials.

Nonetheless, the variant of the conflict adaptation account that Yeung et al. (2011) propose is just one version of the notion that participants adapt to response conflict. As an example of a different version, Botvinick et al. (1999) suggested that “compatible trials are unlikely to induce conflict, regardless of context” (p. 180). This version suggests that there is inherently more conflict in incongruent relative to congruent trials, which might help to explain why there was an effect of previous congruency on the congruency effect independent of previous RT. This version might also predict a stronger effect of previous RT following incongruent trials (wherein conflict is relatively high) than following congruent trials (wherein conflict is relatively low), which we did not observe. However, yet another version of the notion that participants adapt to response conflict suggests that attention is widened in response to the absence of conflict on congruent trials, rather than narrowed in response to the presence of conflict on incongruent trials (Compton, Huber, Levinson, & Zheutlin, 2012; Lamers & Roelofs, 2011). This version might therefore better explain why previous-trial RT influences the congruency effect to a greater degree when the previous trial was congruent as compared to incongruent. In sum, depending on the version considered, the conflict adaptation account may also be able to explain the present findings.

Finally, it might be possible to explain the present findings by combining the conflict adaptation mechanism with the attentional wandering mechanism (or something similar), analogous to the way in which we combined the temporal learning mechanism with the attentional wandering mechanism. For instance, such an adaptation-wandering account might combine the assumption that previous RT is a measure of experienced conflict (Yeung et al., 2011) with the assumption that attention to the distractor varies slowly across time. As in our account, the wandering mechanism in the adaptation-wandering account would magnify the relationship between previous congruent-trial RT and the current-trial congruency effect, while reducing the relationship between previous incongruent-trial RT and the current-trial congruency effect. This variant of the conflict adaptation account might therefore explain not only the CSE, but also some of the higher-order interactions we observed. Future modeling research could be aimed at more formally investigating this possibility.

As the text above indicates, it is possible that a variant of the conflict adaptation account can explain the present results. It is also possible that conflict adaptation explains some of the observed effects, and that other processes (e.g., attentional wandering) account for the remaining patterns of data. Thus, the present results do not rule out a role for conflict adaptation in engendering the CSE. What they do provide, however, is a demonstration that there is cause for concern in interpreting the CSE as solely reflecting conflict adaptation, even in experiments that are not biased by contingencies and feature repetitions. Other explanations (e.g., temporal learning) remain viable.

Limitations

One limitation of the present study is that previous RT did a much better job of explaining the simulated CSE in the modeled data than of explaining the CSE in the human participant data. That is, the PEP model produced a CSE in the standard analysis, but once previous RT was added to the LME model the CSE was considerably reduced. Of course, the CSE is supposed to be reduced by adding previous RT to the model according to the temporal learning account. However, this effect was more pronounced in the simulated data than in the human participant data.

Nonetheless, the PEP model did produce a CSE independent of previous RT in Analysis 3. However, variance in the CSE explained by previous RT still differed between the model and the participant data. This finding suggests two possible interpretations. First, the parameters (or precise mechanisms) of the computational model may have lacked precision. Perhaps with better parameters or with an adjustment in the way the model calculates temporal expectancies, the simulated data would have matched the participant data even better than it did. Second, expectations about congruency may have played a role in producing the CSE, as initially proposed by Gratton et al. (1992; see also the congruency switch cost hypothesis; Hazeltine et al., 2011; Schmidt, 2014; Schmidt & De Houwer, 2011). Such an interpretation might explain why there was an effect of previous congruency on the CSE independent of previous RT. It would also be consistent with recent data, indicating a significant CSE can be observed following RT-matched congruent and incongruent trials (Weissman & Carp, 2013).

A second limitation of the present work is that the temporal learning account does not clearly explain why CSEs can be observed independent of feature repetition and contingency confounds in our prime-probe tasks, but not in the classic Stroop and flanker tasks (e.g., Schmidt &

De Houwer, 2011; but see Duthoo et al., 2014). One possible explanation is that pre-presentation of the distractor in the prime-probe task enables participants to better judge when the upcoming target will appear (because the distractor appears at a predictable interval beforehand), which helps participants to lower the response threshold at the appropriate time (Weissman, Egner, Hawks, & Link, 2015). Another possible explanation is that our prime-probe task prevents feature repetitions by design. Although feature repetitions were not analyzed in the above-mentioned studies, they were still present in the task. Feature repetitions speed some trials substantially (e.g., complete repetition trials by as much as 200 ms), potentially making the timing of responses across trials less predictable. This might cause the temporal expectancy mechanism to fail, because temporal learning is likely most effective when response timing is predictable. Future studies could be conducted to directly investigate these possibilities.

Given the considerations above, we acknowledge that a simple temporal learning account may not fully account for the CSE. One advantage of this account, however, is parsimony. While the PEP model is not less computationally complex than the conflict monitoring model, it proposes that the CSE reflects the operation of non-controversial contingency and temporal learning processes, rather than that of additional conflict monitoring and attentional adaptation processes. These contingency and temporal learning processes are thought to explain a wide range of basic learning phenomena. Indeed, as outlined in Introduction, knowledge about time and contingency is the most fundamental requirement for learning about the world around us. Critically, due to the operation of these non-controversial learning processes, participants are biased to respond with a rhythmic pace that engenders a CSE. Thus, a simple temporal learning account in which the CSE is an incidental result of non-controversial learning processes appears maximally parsimonious. In contrast, proposing the addition of a mechanism that monitors for conflict and yet another that alters the distribution of attention to stimulus features in response to this conflict may add unnecessary complexity. The simplest account is not always the correct account, however. For this reason, additional research will be needed before drawing any firm conclusions.

Along these lines, a third limitation of the present study is that we cannot exclude the possibility that a mechanism other than temporal learning or conflict adaptation may account for our results. For example, consider the activation-suppression hypothesis (Ridderinkhof, 2002), which is an extension of dual-route models in which different pathways underlie the activation of responses associated with target and distractor stimuli (e.g., Kornblum, Hasbroucq, & Osman, 1990). According to this hypothesis, suppression of the distractor pathway is greater after incongruent relative to congruent trials, resulting in a CSE (Ridderinkhof, 2002). Further, suppression of the response associated with a distractor, which may ramify into suppression of the entire pathway in the next trial, increases with RT in both congruent and incongruent trials (Wylie, Ridderinkhof, Bashore, & van den Wildenberg, 2010). Thus, similar to the temporal learning account, the activation-suppression hypothesis appears to predict both a CSE and that the current-trial congruency effect will be larger when previous RT was fast (low suppression) relative to slow (high suppression). Bolstering this possibility, suppression influences performance more when a distractor appears prior to a target (as in our prime-probe tasks) relative to simultaneously with a target (as in more typical Stroop and flanker tasks), likely because presenting a distractor before a target allows suppression of the response associated with the distractor to begin earlier in each trial (Burle, van den Wildenberg, & Ridderinkhof, 2005). Without a formally specified model, however, it is difficult to know whether the activation-suppression account can effectively explain the complex pattern of results observed in Analysis 1. Future computational modeling and experimental research could therefore be aimed at determining whether the temporal learning account, the conflict monitoring account, the activation-suppression account, or some other model best explains the present findings.

Conclusions

This paper presents the novel idea that temporal learning might explain CSEs that are observed after controlling for feature repetition and contingency learning biases. Consistent with this proposal, our findings suggest that a temporal learning mechanism provides a plausible account of the CSE in the prime-probe task, especially if it is assumed that attention to the distractor "waxes and wanes" gradually over trials. The conflict adaptation account does have intuitive appeal, however, and may still explain a part of the CSE in paradigms that do not contain feature integration or contingency learning biases, such as the one employed here. The present findings, however, suggest that it is important for researchers to entertain the possibility that other mechanisms besides conflict adaptation can explain the CSE. Indeed, even if conflict adaptation explains part of the CSE, considering other possible mechanisms, such as those explored in the present manuscript, may eventually lead to the discovery of important new processes that influence behavior.

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