The Parallel Episodic Processing (PEP) Model: Dissociating Contingency and Conflict Adaptation in the Item-Specific Proportion Congruent Paradigm

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Abstract

The present work introduces a computational model, the Parallel Episodic Processing (PEP) model, which demonstrates that contingency learning achieved via simple storage and retrieval of episodic memories can explain the item-specific proportion congruency effect in the colour-word Stroop paradigm. The current work also presents a new experimental procedure to more directly dissociate contingency biases from conflict adaptation (i.e., proportion congruency). This was done with three different types of incongruent words that allow a comparison of: (a) high versus low contingency while keeping proportion congruency constant, and (b) high versus low proportion congruency while keeping contingency constant. Results demonstrated a significant contingency effect, but no effect of proportion congruence. It was further shown that the proportion congruency associated with the colour does not matter, either. Thus, the results quite directly demonstrate that ISPC effects are not due to conflict adaptation, but instead to contingency learning biases.

The Parallel Episodic Processing (PEP) Model: Dissociating Contingency and Conflict Adaptation in the Item-Specific Proportion Congruent Paradigm

For decades, one of the most popular ideas in the cognitive psychology literature is the idea that participants are able to adapt to conflict encountered in performance tasks such as the Stroop by adjusting attention away from the source of conflict. Perhaps the most popular instance of purported conflict adaptation is the proportion congruent effect. In the Stroop task (Stroop, 1935), participants are slower to identify the colour of a colour word when the word is incongruent (e.g., the word RED printed in blue; RED_{blue}) relative to when it is congruent (e.g., RED_{red}). This congruency effect is larger when the proportion of congruent trials in the task is high (e.g., 75% congruent, 25% incongruent) relative to when the proportion of congruent trials is low (e.g., 25% congruent, 75% incongruent; Lowe & Mitterer, 1982). This interaction between congruency and proportion congruency, termed the proportion congruent (PC) effect, is generally interpreted as evidence of conflict adaptation (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001; Cheesman & Merikle, 1986; Lindsay & Jacoby, 1994). Specifically, it is argued that the congruency effect is smaller in the low PC condition because participants detect that most of the trials in the task are conflictual (i.e., incongruent) and thus direct their attention away from the distracting word to avoid further conflict. As a result, the word has less impact on performance, resulting in a smaller Stroop effect.

Although the conflict adaptation idea is highly intuitive there are reasons to doubt this explanation of the proportion congruent effect. One challenge was presented by Jacoby, Lindsay, and Hessels (2003) when they introduced an item-specific version of the proportion congruency paradigm. Instead of manipulating PC between-participant or between-block, they manipulated PC across items. For example, BLUE and GREEN may have been presented most often in their congruent colour (high PC), whereas RED and ORANGE might have been presented most often in their incongruent colour (low PC). Participants produced a larger congruency effect for high relative to low PC items, what has been termed an item-specific proportion congruent (ISPC) effect. The ISPC effect poses some difficulty for the conflict adaptation account. If participants are detecting how much conflict they encounter in the *task*, then it is not clear how they would be able to adapt to conflict differently for high versus low PC *items*, which are intermixed in the task. Although claims have been forwarded that participants can learn the conflict associated with individual items and rapidly adjust attention accordingly (e.g., Blais, Robidoux, Risko, & Besner, 2007; Verguts & Notebaert, 2008), there is another potential explanation that does not rely on conflict adaptation at all.

A drastically different interpretation of the ISPC effect (and PC effects in general) was presented by Schmidt and colleagues (Schmidt & Besner, 2008; Schmidt, Crump, Cheesman, & Besner, 2007; see also, Mordkoff, 1996). According to these authors, participants might simply be learning the contingencies between distracting words and responses to the colour. Participants then respond faster to these *high contingency* trials (i.e., where the word is predictive of the correct response) relative to *low contingency* trials (i.e., where the word is *not* predictive of the correct response). In non-conflict tasks, such contingency effects are found to be quite reliable (see Schmidt, 2012). For example, Miller (1987; see also Carlson & Flowers, 1996) found that when distracting letter flankers were predictive of the target letter, high contingency trials are faster than low contingency trials. Similarly, Schmidt and colleagues (2007) found a contingency effect when distracting neutral words were predictive of the colour they were printed in (e.g., MOVE most often in blue). Such contingency biases can explain the ISPC effect. For example, if GREEN is presented most often in green, then the word GREEN is accurately predictive of the green response. Thus, congruent trials in the high PC condition will be speeded, leading to a larger Stroop effect. Similarly, if RED is presented most often in yellow, then RED is accurately predictive of the yellow response. Thus, *incongruent* trials will be speeded in the low PC condition leading to a *smaller* Stroop effect. It can therefore be seen that contingency biases alone will produce a congruency by proportion congruency interaction (i.e., PC effect). Note that response conflict is still assumed to exist according to the contingency account, but the changes in the size of the Stroop effect with differing levels of PC has to do with the predictive relationships between words are responses and not due to variation in conflict per se.

Schmidt and Besner (2008) suggested that participants learn the predictive relationships (i.e., contingencies) between words and responses to prepare for the likely (i.e., high contingency) response. In particular, they suggested that participants calculate the expected response based on the identity of the word and use this response prediction to decrease the response threshold of the predicted response. An even simpler explanation is that “contingency learning” is simply a by-product of memory storage and retrieval processes (see Schmidt, De Houwer, & Besner, 2010). Specifically, on each trial participants encode information about what stimuli (word and colour) were presented along with what response was made into an episodic memory. On subsequent trials, presentation of the word will lead to retrieval of past episodes of when this word was presented, which then directly facilitate the high contingency response associated with these episodes. The Parallel Episodic Processing (PEP) model, described in the section to follow, does exactly this.

The PEP model will provide computational support for this new episodic retrieval account of the ISPC effect. In addition, the PEP model will be used to investigate an important question about additivity. Specifically, Schmidt and Besner (2008) argued that contingency and congruency effects are due to statistically-independent processes and should generally not interact with each other. This paper will argue that this additivity prediction is mistaken. However, the argument that Schmidt and Besner put forward is that the *high contingency* congruent (high PC) and incongruent (low PC) trials will both be responded to roughly equally faster than *low contingency* congruent (low PC) and incongruent (high PC) trials, respectively. As a result, the benefit of high contingency is equivalent for congruent and incongruent trials, meaning that contingency and congruency should not interact. Schmidt and Besner provided data consistent with this notion. These additivity predictions contrast sharply with those that would be expected from a conflict adaptation account that should anticipate all fluctuation in the size of the congruency effect to be due to changes in incongruent (and not congruent) trials, given that the Stroop effect is almost entirely an interference phenomenon (e.g., see MacLeod, 1991, for a review). Schmidt and Besner thus suggested that the interaction pattern (i.e., additive vs. interaction) could be used to distinguish between contingency learning and conflict adaptation.

The additive pattern of data observed by Schmidt and Besner (2008) is indeed problematic for the conflict adaptation account of the ISPC when observed. However, there is a problem with the prediction that contingency and congruency should always be additive. Even if it is true that contingency and congruency effects are due to independent processes, it does not necessarily follow that the two effects will be perfectly additive (and, indeed, they are not in all task variants; e.g., Bugg, Jacoby, & Chanani, 2011). For example, incongruent trials take longer to respond to than congruent trials, so there is more time on an incongruent trial for contingencies to bias responding relative to a congruent trial. This would result in a larger contingency effect for incongruent relative to congruent trials, producing an overadditive interaction.[1] Thus, even if the contingency account of ISPC effects is correct, deviation from the additive pattern Schmidt and Besner demonstrated is likely, particularly with higher power experiments and in situations that promote this sort of overadditive interaction (e.g., where responses to congruent trials are restricted by a floor effect). In this vein, a second goal of Simulation 1 is to see whether a model that produces an ISPC effect via contingency learning processes rather than conflict adaptation produces results that deviate from additivity.

Stimulation 1

A visual representation of the PEP model is presented in Figure 1. A simplified explanation of the model is explained in the text to follow, but for interested readers a complete conceptual overview and description of the math of the model is presented in the Appendix. Fully documented source code is available online (http://users.ugent.be/~jaschmid/PEP/) or from the author.

(Figure 1 about here)

The primary goal of Simulation 1 is to demonstrate that a very simple episodic memory model can account for the ISPC effect. On each trial, the model creates a new episode, which is linked to activated words. Activation from word and colour Input nodes competes in Identity nodes, thus producing a congruency effect. Words also activate Episode nodes, which in turn activate Response nodes (note that colours are not linked to episodes for computational simplicity only). As the episodes associated with a particular word are most often associated with a specific (high contingency) response, these processes result in the high contingency Response node being active, thus producing a contingency effect. The model has no mechanism by which it can learn about and adapt to conflict. Response conflict does occur in the model (i.e., if two or more Identity nodes are active, then they will compete), but the model is unable to measure this conflict (conflict monitoring) or adjust attention or other processing in response to conflict

(conflict adaptation).

Method

Simulation 1 was basically identical to the design of Jacoby and colleagues (2003). There were four pairs of colours. High and low PC trials were completed in one run and medium PC trials were completed in a second run (they were two separate blocks in original experiment). In the first of these two runs, two of the words were presented three of four times in their congruent colour (high PC) and once in the other (incongruent) colour, whereas the other two words were presented three of four times in a specific incongruent colour (low PC) and once in their congruent colour. In the second run, two pairs of words were presented equally often (two of four times) in both the congruent and incongruent colour (medium PC). The model was run 1000 times (i.e., 1000 "participants"), with 16 trials in each of 30 blocks, for a total of 480 trials.

Results

Cycle times. The results of Simulation 1 can be seen in Figure 2. The PEP produced an overall congruency effect of 89 cycles. The model also produced an ISPC effect: the congruency effect was 117 cycles in the high PC condition, 90 cycles in the medium PC condition, and 61 cycles in the low PC condition. Most importantly, deviation from additivity was apparent. When the results were plotted as a function of contingency (Figure 2b) rather than PC, the congruency effect was 68, 90, and 110 cycles in the high, medium, and low contingency conditions, respectively. Thus, an overadditive interaction was observed.

(Figure 2 about here)

Error percentages. The error data for Simulation 1 are presented in Figure 3. The model produced an overall congruency effect of 2.2%. The model also produced an ISPC effect: the congruency effect was 2.7% in the high PC condition, 2.2% in the medium PC condition, and

1.7% in the low PC condition. Most importantly, deviation from additivity was again observed. When the results were plotted as a function of contingency rather than PC, the congruency effect was 1.9, 2.2, and 2.5% in the high, medium, and low contingency conditions, respectively. Thus, an overadditive interaction was again observed.

(Figure 3 about here)

Discussion

The results of Simulation 1 demonstrate two things. First, memory encoding and retrieval processes are sufficient to produce an ISPC effect. Like conflict monitoring models (e.g., Blais et al., 2007; Verguts & Notebaert, 2008), the PEP successfully simulated the ISPC effect in both cycle times and error percentages. Thus, conflict monitoring and adaptation do not need to be assumed to simulate the ISPC effect. Second, the results were not perfectly additive. Specifically, the contingency effect was larger for incongruent relative to congruent trials. As discussed in the introduction, this is due to the fact that contingency has more time to influence responding on incongruent relative to congruent trials. The degree to which the results do or do not deviate from additivity can be altered by playing with parameters, many of which might correspond to differences between experiments (e.g., speeding target identification, similar to Bugg et al., 2011). Deviation from additivity was also found with an earlier version of the model that more closely corresponded to the response threshold idea of Schmidt and Besner (2008). Thus, the contingency account of the ISPC can tolerate such overadditive interactions, contrary to what Schmidt and Besner suggest. An interaction between contingency and congruency cannot therefore be used to argue against a contingency account, as Schmidt and Besner previously suggested. Thus, a new dissociation procedure is required to distinguish between conflict adaptation and contingency.

Experiment 1

Schmidt and Besner (2008) previously argued that additive results support the contingency account and overadditive results support the conflict adaptation account. Simulation 1 demonstrates that this is not necessarily true. Logically, independent processes do not entail additive data and Simulation 1 clearly demonstrated that the contingency account can tolerate non-additivity. Given that overadditivity is also consistent with conflict adaptation theory, it is difficult to interpret such non-additive patterns. For example, if one finds an overadditive interaction driven solely by incongruent trials, then is this another contingency bias or legitimate conflict adaptation? A new approach is therefore needed.

A more direct approach to assessing contingency biases in the ISPC task is to dissociate item-level proportion congruence from contingency. This was the goal of Experiment 1. As can be seen in Table 1, the design had four colour words, two of which were high PC (BLUE and GREEN) and two of which were low PC (RED and YELLOW). Critically, some of the low PC incongruent items were high contingency (e.g., $\text{RED}_{\text{yellow}}$), whereas others were low contingency (e.g., RED_{blue}). These manipulations allow the creation of three incongruent trial types, each shaded differently in Table 1: (1) high contingency/low PC (high/low) such as $\text{RED}_{\text{yellow}}$, (2) low contingency/low PC (low/low) such as RED_{blue}, and (3) low contingency/high PC (low/high) such as $\text{BLUE}_{\text{green}}$. In most ISPC designs, only high/low and low/high incongruent trials are present, thus directly confounding contingency and PC. The inclusion of the low/low incongruent trials is thus critical in dissociating contingency and PC effects. Specifically, the high/low and low/low incongruent trials vary only in contingency (i.e., they are both low PC), making a difference between the two evidence for a contingency learning contribution to the ISPC effect. In contrast, low/low and low/high incongruent trials vary only in PC (i.e., they are both low contingency), making a difference between the two evidence for conflict adaptation.

(Table 1 about here)

Recently, Bugg and colleagues (2011) have suggested that sometimes the proportion congruency of the colour (rather than the word) might matter. Although the experimental setup of the current experiment is probably not ideal for matching the parameters suggested by those authors for when colour PC might matter (specifically, when the colour has a processing advantage over the word), a dissociation of colour PC independent of word PC (i.e., the typical PC measure) and contingency was provided. This was achieved by separating low/high incongruent trials into two subtypes. Of the six low/high incongruent trials in Table 1, it can be seen that two of these have a high PC colour (i.e., $\text{BLUE}_{\text{green}}$ and $\text{GREEN}_{\text{blue}}$), whereas the remaining four have a low PC colour (i.e., BLUE_{red}, $\text{BLUE}_{\text{yellow}}$, $\text{GREEN}_{\text{red}}$, and $\text{GREEN}_{\text{yellow}}$). Both of these trial types are low contingency and have a high PC *word* (i.e., BLUE or GREEN), so they vary only in the PC of the *colour*. Thus, these manipulations allow an assessment of contingency, word PC, and colour PC independently.

Method

Participants. Fifty Ghent University undergraduates participated in exchange for course credit.

Apparatus. Stimulus and response timing were controlled by E-Prime software (Psychology Software Tools, 2002). Responses were made on an AZERTY keyboard.

Materials and Design. Stimuli were presented on a black background. There were four Dutch colour words (blauw [blue], groen [green], rood [red], and geel [yellow]) presented in the same four display colours (blue, green, red, and yellow). Words were presented in lowercase, bold, 18 pt. Courier New font. The RGB values for the colours were 0,0,255 (blue), 0,255,0 (green), 255,0,0 (red), and 255,255,0 (yellow). A total of 400 stimuli were selected randomly with replacement. Two colour words were presented 70% of the time in their congruent colour (high/high congruent) and equally often in the remaining three colours (low/high incongruent). The other two colour words were presented 70% of the time in the other low PC colour (high/low incongruent) and equally often in the remaining three colours (low/low congruent and incongruent).

Procedure. Participants sat approximately 60 cm from the screen. They were first presented with a white fixation ("+") for 250 ms, followed by a blank screen for 750 ms, followed by the Stroop stimulus for 2000 ms or until a response was made. The next trial began immediately after correct responses. Trials on which an error was made or the participant failed to respond in time were followed by "XXX" in white for 500 ms before the next trial. Responses were made with the U, I, O, and P keys. Which colour was mapped to which key was randomly determined for each participant. The PC level associated with each colour was also randomized. Which keys corresponded to high or low PC colours was counterbalanced across participants.

Results

Correct response latencies and errors were analysed. Two participants were dropped from the analysis for failing to comply with instructions. One had almost 100% errors in the three incongruent conditions, indicating that they were responding to the word rather than the colour. The second participant that was deleted made the same mistake for the first half of the experiment and resultantly had over 50% errors in the three incongruent conditions.

Response Latencies. First, the ISPC effect was assessed in the traditional way by performing a 2 congruency (congruent vs. incongruent) x 2 PC (high vs. low) ANOVA. Unsurprisingly, there was a significant main effect of congruency, $F(1,47) = 147.474$, MSE =

2477, $p < .001$, $\eta_p^2 = .76$, indicating slower overall responses to incongruent trials. There was no main effect of PC, $F(1,47) = .025$, $MSE = 3498$, $p = .874$, $\eta_p^2 < .001$. Critically, there was a significant interaction between congruency and PC (i.e., an ISPC effect), $F(1,47) = 21.444$, $MSE = 2612$, $p < .001$, $\eta_p^2 = .31$.

Next, the three types of incongruent trials were divided up and the two critical tests were completed. Responses were significantly faster to high/low (775 ms) relative to low/low (815 ms) incongruent trials, $t(47) = 3.409$, $SE_{diff} = 12$, $p = .001$, $\eta_p^2 = .20$, indicating a significant contingency effect. In contrast, no difference was found between low/low and low/high (818 ms) incongruent trials, $t(47) = .319$, $SE_{diff} = 10$, $p = .751$, $\eta_p^2 < .01$, indicating no evidence for conflict adaptation. Further, this test had high power (.98) to detect an effect as large as the observed contingency effect. The potential effect of the PC of the colour was then assessed by separating low/high incongruent trials and no significant difference was found between high PC colours (815 ms) and low PC colours (820 ms), $t(47) = .302$, $SE_{diff} = 17$, $p = .764$, $\eta_p^2 < .01$. Indeed the means were numerically in the wrong direction. Finally, high/high congruent trials (697 ms) were responded to significantly faster than low/low congruent trials (730 ms), $t(47) = 2.437$, $SE_{diff} = 13$, $p = .019$, $\eta_p^2 = .11$, consistent with either account.

Error Percentages. The 2 congruency (congruent vs. incongruent) x 2 PC (high vs. low) ANOVA for errors revealed a significant main effect of congruency, $F(1,47) = 17.985$, $MSE = 25$, $p < .001$, $\eta_p^2 = .28$, indicating more errors overall for incongruent trials. There was no main effect of PC, $F(1,47) = .599$, $MSE = 15$, $p = .443$, $\eta_p^2 = .01$. Critically, there was a significant interaction between congruency and PC (i.e., an ISPC effect), $F(1,47) = 10.323$, $MSE = 15$, $p =$

.002, $\eta_p^2 = .18$.

The errors were generally less sensitive than the response latencies. There were no significant differences between high/low (7.2%) and low/low (7.7%) incongruent trials, $t(47) = .476$, $SE_{diff} = 1.0$, $p = .637$, $\eta_p^2 < .01$, low/low and low/high (9.5%) incongruent trials, $t(47) = 1.823$, $SE_{diff} = 1.0$, $p = .075$, $\eta_p^2 = .07$, high PC colours (9.5%) and low PC colours (9.6%), $t(47) = .095$, $SE_{diff} = 1.1$, $p = .925$, $\eta_p^2 < .001$, or high/high (4.6%) and low/low congruent trials (6.0%), $t(47) = 1.489$, $SE_{diff} = .9$, $p = .143$, $\eta_p^2 = .05$. Thus, errors were largely uninformative.

Discussion

The results of the Experiment 1 found clear support for the contingency account of ISPC effects and no support for conflict adaptation. Support for the contingency account was found in the observation of a contingency learning effect when PC was controlled for (i.e., high/low vs. low/low). A difference between these two conditions can only be attributable to contingency learning. Hutchison (2011) recently performed a similar test in verbal Stroop data, where a contingency learning contribution was also confirmed.[2] Experiment 1 also tested for a contribution of the item-level PC of the word (i.e., low/low vs. low/high). The conflict adaptation account would predict greater interference for low/high relative to low/low incongruent trials, but no difference was observed.[3] Furthermore, the PC of the colour also did not affect performance.

General Discussion

This work provides three key new contributions. First, Simulation 1 with the Parallel Episodic Processing (PEP) model demonstrates that very simple memory storage and retrieval processes can produce an ISPC effect. The processes involved in this model are even simpler than the response prediction and threshold adjustment ideas of Schmidt and Besner (2008). All the model does is store episodic memories of trials (i.e., memories of the stimuli and responses that occurred on the trial) and then retrieve these memories on subsequent trials. These highly simple processes were sufficient to produce an ISPC effect. Of course, sufficiency does not prove that contingencies are the whole story. Conflict monitoring models can also produce the ISPC effect (Blais et al., 2007; Verguts & Notebaert, 2008) and the current simulation does not preclude the possibility that both contingency and conflict monitoring biases are present in the task. Experiment 1, however, has more to say on that point.

In addition to providing an existence proof that episodic memory biases can produce an ISPC effect without appealing to the notion of conflict adaptation, the PEP model makes a second key contribution. The results of Simulation 1 show that contingency learning biases are not necessarily always additive with congruency. Instead, contingency effects will often be larger for incongruent relative to congruent trials. This is because contingency has more time to affect behaviour on incongruent trials. Indeed, finding parameters that allow for additive-looking data was challenging. This might indicate that some deviation from additivity will *always* be present (but not necessarily big enough to detect statistically). Alternatively, it could simply mean that the current configuration of the PEP model is too cascaded. A change in the rules of how activation is passed from one set of nodes to another could affect the degree of additivity. In future work, investigating such parameters might prove important. For the current work, it is sufficient to point out that contingency learning can produce overadditive effects of contingency and congruency.

Even if contingency learning and Stroop conflict are due to independent processes, it does not follow that their effects will be additive, contrary to what Schmidt and Besner (2008) suggested. It may, however, be that congruency and contingency effects are at least roughly additive in many experimental setups. This is because contingencies affect both congruent and incongruent trials. An overadditive interaction only occurs to the extent that contingencies affect congruent and incongruent trials to a different magnitude. When additive data *is* observed, it is difficult to explain such results within the context of a conflict adaptation account of ISPC effects. Specifically, it is unclear why increased attention to the word should have any beneficial effect for congruent trials when the Stroop effect is known to be almost (or perhaps completely) attributable to interference and not facilitation (see MacLeod, 1991, for a review). However, deviation from strict additivity is likely in many situations even if the contingency account of ISPC effects is correct. This fact forces a different approach to distinguish contingency biases from conflict adaptation (i.e., one that does not rely on determining the interaction type).

Related to this, the third key contribution of this work is a more effective way of distinguishing between contingency learning and conflict adaptation. Rather than relying on the interaction pattern (i.e., additive vs. interactive), Experiment 1 used a dissociation procedure in order to assess contingency learning and conflict adaptation biases separately. This analysis found evidence for contingency learning, but not for conflict adaptation. Thus, the present results suggest that conflict adaptation effects do not occur in the ISPC task, or are very small and difficult to observe. Given this low reliability, it is unclear whether the ISPC paradigm is a suitable metric for studying conflict adaptation. It is also challenging to completely control for contingency biases. For example, while Experiment 1 determined a way to deconfound incongruent trials, congruent trials are inherently confounded: high PC congruent words are high contingency and low PC congruent words are low contingency (for similar problems with the Gratton paradigm, see Schmidt & De Houwer, 2011).

It is important to highlight the fact that the current work concerns itself with *item-specific* proportion congruent effects. Recent work has indicated that *list-level* proportion congruent effects are also observable (e.g., Hutchison, 2011). That is, after accounting for item-specific learning, participants are responsive to the proportion of congruent trials in the task as a whole. List-level PC effects cannot be explained by a contingency learning mechanism. It could therefore still be the case that list-level PC effects are driven by conflict adaptation (but see, Schmidt & De Schryver, 2012). List-level conflict adaptation would not require the same rapid, trial-by-trial shifts in attention proposed for item-level conflict adaptation and thus might be more psychologically plausible.

On a similar note, context-level conflict adaptation might also be possible in some situations (e.g., Bugg, Jacoby, & Toth, 2008; Crump, Gong, & Milliken, 2006). That is, a contextual cue such as stimulus font could serve as a cue to conflict. Context-level conflict adaptation might be possible because participants can use a rapidly-processed initial distracting cue (e.g., font) to determine the PC associated with another distracting cue (e.g., word). This sort of conflict adaptation would be much different (and probably easier) than using a distracting cue (e.g., word) to determine the PC associated with itself as the trial unfolds. Admittedly, item-specific conflict adaptation accounts seem a bit counterintuitive (e.g., because you determine how to attend to something based on its own identity, which obviously cannot be known before attending to it), whereas list- or context-level conflict adaptation seems much less unintuitive (i.e., because you determine how to attend to something based on separate contextual information). Further work is certainly required to disentangle these complexities.

In summary, this paper argued that interpretation of interaction patterns is a suboptimal way of differentiating contingencies and conflict adaptation. Instead, focus on direct dissociations between contingency and PC, such as Experiment 1 in the current paper, is desirable for future work. Looking forward, further attempts to uncover previously-unidentified confounds in the varied paradigms used for studying conflict adaptation could prove quite beneficial to the literature. For example, list-level and context-level PC effects could be due to conflict adaptation, but they could also be due to temporal learning (Schmidt & De Schryver, 2012). Indeed, one of the tough challenges for all researchers publishing in the conflict adaptation domain is to explain the inconsistencies between the results that do seem to suggest conflict adaptation and the results that fail to find evidence for conflict adaptation when confounds are rigorously controlled for. Is conflict adaptation merely context-sensitive? What rules determine when it comes and goes? Answering such questions could be highly informative. Conflict adaptation theory may yet stand the test of time, though perhaps in a much more restricted form than initially thought.

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Footnotes

[1] This point was initially included in Schmidt and Besner (2008), but was later regulated to a footnote and eventually omitted from the manuscript entirely.

[2] While Hutchison did not compare high/low and low/low incongruent trials directly, the Stroop effects for these incongruent trial types were compared using the same congruent trials as a baseline. Thus, this test was effectively identical to the analyses in the current paper.

[3] The design of Hutchison also had low/high incongruent trials. However, these were not directly compared with low/low incongruent trials. Furthermore, such a direct comparison in that study could probably be considered questionable given that: (a) the strength of the contingencies associated with high and low PC words was not identical, and (b) low PC words had above-chance contingencies with both the congruent response and one incongruent response, whereas high PC words had above-chance contingencies with only one response (i.e., the congruent one).

Table 1. Frequency of word colour pairings in Experiment 1.

	BLUE	GREEN	RED	YELLOW
blue	7	1	1	1
green	1	7	1	1
red	1	1	1	7
yellow	1	1	7	1

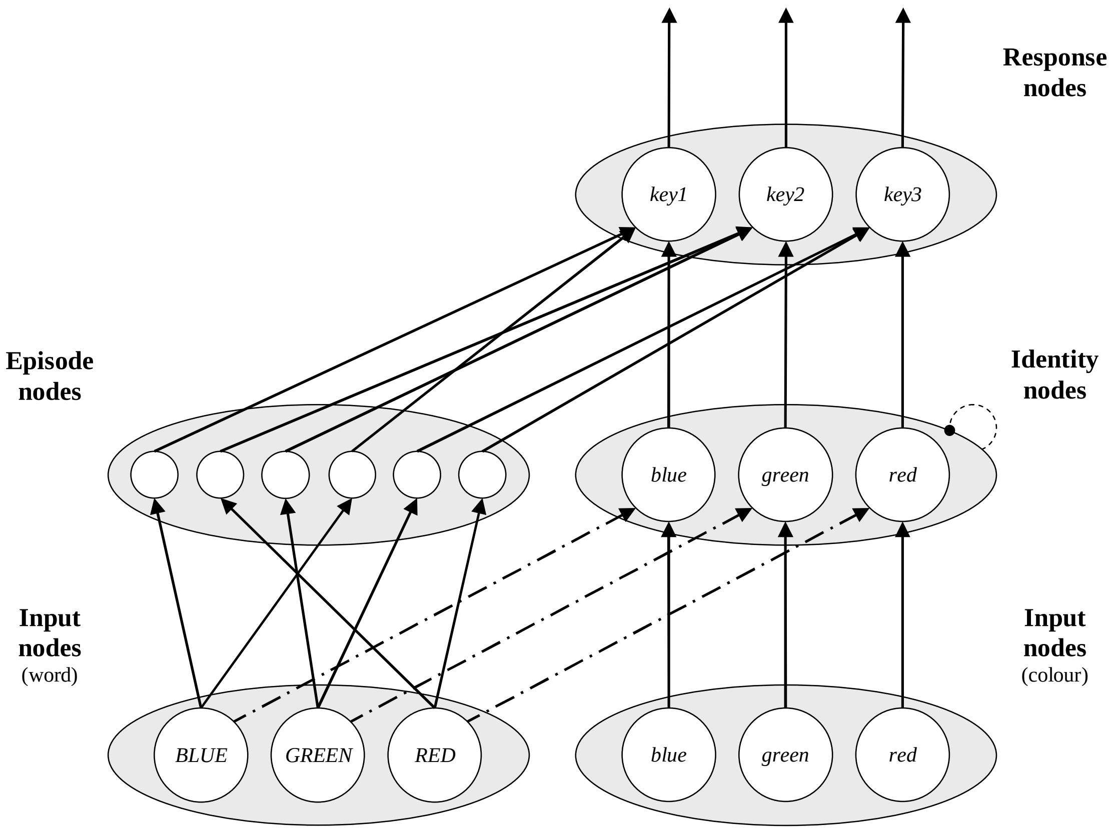
Note: The three incongruent trial types are shaded (light grey = low/high, medium grey = low/low, and dark grey = high/low).

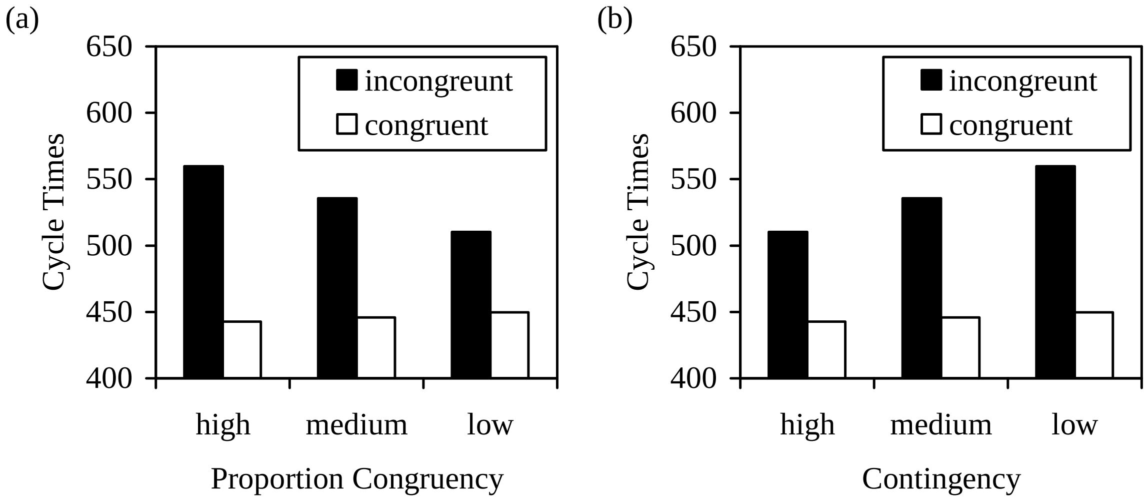
Figure

Figure 1. A pictorial representation of the PEP. Input nodes for colours feed into Identity nodes, which then feed into Response nodes. Input nodes for words feed into Episode nodes (one for each experienced trial), which then feed into Response nodes, producing contingency learning. Input nodes for words also feed into Identity nodes, where word-colour conflict occurs. Note that Input nodes for colours are not connected to Episode nodes for simplicity in modelling only (and because such connections were not relevant for the current simulation).

Figure 2. Simulation 1 cycle time data with congruency as a function of (a) proportion congruency and (b) contingency.

Figure 3. Simulation 1 percentage error data with congruency as a function of (a) proportion congruency and (b) contingency.


Response
nodes
key1
key2
key3
Episode
nodes
Identity
nodes
blue
green
red
Input
nodes
(word)
Input
nodes
(colour)
BLUE
GREEN
RED
blue
green
red


(a)
650
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Cycle Times
incongreunt
congruent
high
medium
low
Proportion Congruency
(b)
650
600
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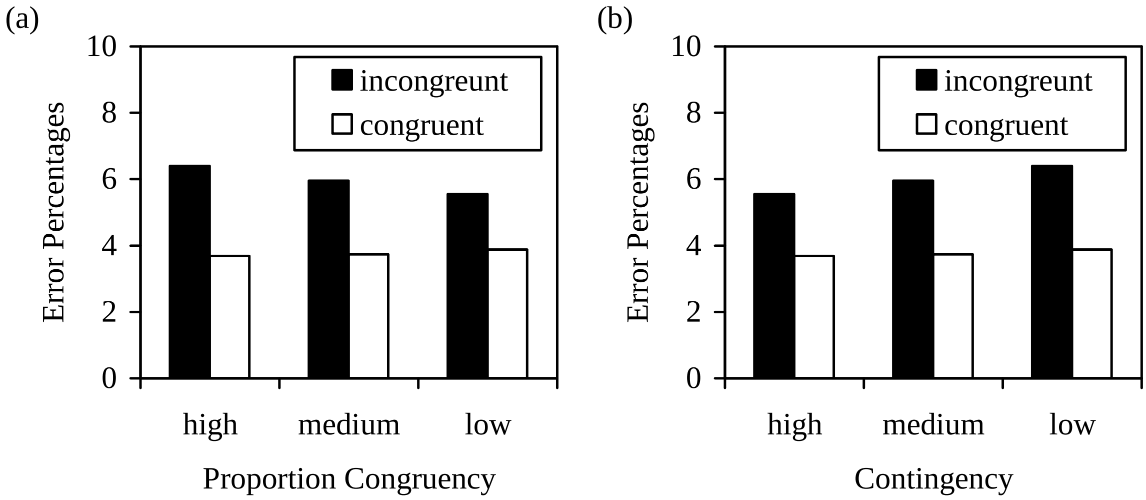
500
450
400
Cycle Times
incongreunt
congruent
high
medium
low
Contingency


(a)
10
8
6
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Error Percentages
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Proportion Congruency
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congruent
high
medium
low
Contingency

Appendix: Model Description

Input

Similar to the conflict monitoring models, the PEP has an Input node for each word and each colour. On each processing cycle of each trial, all Input nodes in the PEP receive an input that is determined with the formula,

$$input_i = (bias_i + noise) / 2 \qquad (1)$$

For each node *i*, a random *bias* is set at the beginning of each trial between 0 and .9. The *noise* parameter is randomly determined on each processing cycle as number between 0 and 1. The *bias* parameter is adjusted by .4% on each cycle toward the *signal* value of .9 for presented items and 0 for non-presented items. Thus, the model slowly adjusts toward the correct response over time, meaning that over time the model will always give the correct response, but not if speeded (i.e., much like actual participants).

The *input* value determined with Formula 1 is used to update the activation state of the node on each processing cycle using the formula,

$$activation_i = activation_i(1 – decay) + input_i(decay) \qquad (2)$$

Using this formula, *activation* approaches the value of *input* across processing cycles. The *decay* parameter was set at .01. Inter-trial intervals of 300 cycles were inserted before each trial, in which *bias* and *signal* were 0 and *noise* remained 1. Thus, activation quickly decays during the inter-trial interval.

From Input to Response Nodes

For simplicity, colour-to-response mappings are hardwired in the PEP. Colour and word Input nodes activate intermediate Identity nodes (again, one for each colour), which then activate the Response nodes (one for each response). Both the output from Input to Identity nodes and from Identity to Response nodes is calculated with the formula,

$$output_i = (activation_i - threshold)(noise) \qquad (3)$$

Formula 3, of course, is only calculated when *activation* > *threshold* (set at .3). The *noise* parameter was randomly determined on each processing cycle as a value between 0 and 1 for word Input nodes, 0 and 6 for colour Input nodes, and 0 and 5 for Identity nodes. As with Input nodes, the *input* value for Identity and Response nodes updates activation with Formula 2. Identity nodes also include within-level inhibition of 5% activation of other Identity nodes. This within-level inhibition is what produces the congruency effect.

Episodic Retrieval

Word Input nodes retrieve Episode nodes (described in the following section). Specifically, word Input nodes with activation exceeding the defined *threshold* for retrieval (also set at .3) activate Episodes using the formula,

$$output_i = (activation_i - threshold)(m)(strength_x) \qquad (4)$$

Activation of word Input nodes exceeding the *threshold* is multiplied by a multiplier *m* (set at 6) and the connection *strength* between that word Input node and each Episode *x*. How these connections strengths are determined is explained in the following section.

Episode Encoding

On each trial, the PEP stores a discrete episodic memory (for other episodic models, see Estes, 1986; Hintzman, 1984, 1986, 1988; Logan, 1988; Medin & Schaffer, 1978; Nosofsky, 1988a, 1988b) of the current trial, an Episode node. For each word, a connection *strength* from the word Input node to the current Episode node *x* is made using the formula,

$$strength_x = strength_x(1 - decay) + (activation_i - threshold)(decay) \qquad (5)$$

The *threshold* parameter is the same as the retrieval threshold in Formula 4 (i.e., .3). As can be seen, the connection strength between a word and episode is determined by the extent to which that word was activated on the trial. For example, if the word MOVE was presented, then the *MOVE* Input node will have a strong link to the current episode. Due to noise, other word Input nodes may also have (much weaker) connections to the current episode. Thus, the degree to which a word is activated during episode encoding is directly related to the degree to which it will later serve as an effective retrieval cue. The *strength* with which an Episode node is connected to each Response node is also calculated with Formula 5, except that the *activation* state of the corresponding Response node is used and there is no *threshold*.

Memory Reconsolidation

The PEP also performs memory reconsolidation. It is obviously the case that for memory to work effectively it needs to be able to adapt as new stimuli are experienced. For example, although it may be important to have some memory of the various places you tend to leave your keys, it is most important to remember where you left them last. Thus, an important part of remembering where your keys are now is (partially) forgetting where you left them before. PEP achieves this by inhibiting memories to the extent that they are retrieved using the formula,

$$strength_x = strength_x(1 - (activation_i - threshold)(decay)) \qquad (6)$$

The *decay* parameter for weakening connections is .0001 per cycle and the *threshold* parameter is the same retrieval threshold as in Formulas 4 and 5 (.3). With this formula, the *strength* value of a connection only decreases if *activation* > *threshold*. Thus, unlike simple decay, memories do not weaken merely as a function of time. Rather, memories are weakened in order to accommodate for the encoding of new information. For example, if the word MOVE is presented on a trial, then a new MOVE Episode node will be created and old MOVE Episode nodes will be weakened. Non-MOVE Episode nodes (e.g., SENT Episode nodes) will not be changed.

Although not key for the simulations reported in the current series, this reconsolidation process allows the model to rapidly adapt to changes in contingency (e.g., see Schmidt et al., 2010).

Episode Output

Like all episodic models of memory, the PEP does not learn contingencies while it performs. Rather, the model simply stores memories of trials as it performs the task. “Learning” in an episodic model of memory is what results when information is retrieved from memory. For example, when a participant encounters the distracting word MOVE, they will retrieve several episodic memory traces in which that word was encountered. Because MOVE was presented most often in blue, a large majority of the episodes retrieved will be linked to the blue key response. Thus, the simple act of retrieving episodic memories of trials in which MOVE was encountered is sufficient to bias the cognitive system toward a blue key response. In the computational model, Episode nodes activated above a defined *threshold* (set at .02) add to the *output* of each response using Formula 4, using the same multiplier (m) of 6 and the connection *strength* that was determined with Formula 6, as described in the previous section. Outputs from multiple Episode nodes add up in the *output* value for a particular response.

Response Anticipation

The *output* from Episode nodes determined in the previous step is then put into a retrieval mechanism. The *input* from episodic memory to Response nodes is determined with the formula,

$$input_i = output_i - \left(\left(\sum_{j=1}^{n} output_j - output_i\right) / (n-1)\right) \tag{7}$$

Here, i is the current response and nodes 1 to n are the remaining nodes. If the total incoming activation from all nodes exceeds 1, then the result of Formula 7 is divided by the total incoming activation. A small *threshold* to correct for random biases is then subtracted (set at .1) and the final *input* is then constrained between 0 and .2. Formula 7 ensures that the *input* value of a

Response node will only increase above zero if the incoming activation is greater than the average output to the other Response nodes. This formula allows only the high contingency response to become strongly activated. Note that this retrieval mechanism is in some ways similar to mechanisms used in other episodic computational models for determining, for example, a classification response (e.g., the resonance mechanism of Ratcliff, 1978).