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Modeling graded response congruency effects in task switching ☆

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ABSTRACT

Compound cue retrieval is a computational model of a mediated route for response selection in task-switching situations. In previous studies, the model has been shown to account for response congruency effects when switching between two tasks, where response congruency reflects the degree of match between relevant and irrelevant task responses associated with a target stimulus. In the present study, the author derived a model prediction of graded response congruency effects in situations involving three tasks. The predicted pattern was observed for both response time and error rate in an experiment in which numerical categorization tasks were performed on single-digit targets. Implications for understanding response congruency effects and for developing models of task-switching performance are discussed.

1. Introduction

Task switching is a domain that is ripe for the development and testing of computational models of cognition. As indicated by two recent reviews of the task-switching literature (Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010), there is a large body of empirical findings that has yet to be explained in a comprehensive and integrated manner. The best prospect for an integrated explanation is a computational model that instantiates the cognitive mechanisms involved in task-switching performance. Recognizing this point, many researchers have proposed different models of task switching over the past several years (e.g., Altmann & Gray, 2008; Brown, Reynolds, & Braver, 2007; Gilbert & Shallice, 2002; Schneider & Logan, 2005; Sohn & Anderson, 2001). Unfortunately, many of these endeavors have been one-off efforts, with the models not investigated beyond the original articles in which they were proposed. Consequently, there has been little in the way of cumulative model development in task switching compared with other domains (e.g., Anderson, 2007; Logan, 2004; Perry, Ziegler, & Zorzi, 2007; Shiffrin, 2003).

An exception is the model of compound cue retrieval proposed by Schneider and Logan (2005), which accounts for how responses are selected in task-switching situations. In the original article, the model was used to explain cue–target congruency effects, which reflect the match or mismatch between a categorically biased cue and a target stimulus when performing semantic categorization tasks. In subsequent articles, compound cue retrieval was used to explain priming and response congruency effects (Schneider & Logan, 2009), target functions (Logan & Schneider, 2010), and stimulus-order effects (Schneider & Logan, 2014). The purpose of the present study was to build on this line of work by deriving and testing a prediction about response congruency effects that the model makes when it is applied to a task-switching situation involving three tasks.

1.1. Response congruency effects

A typical task-switching experiment involves two categorization tasks that share a set of responses. For example, one task might involve categorizing single-digit targets as odd or even, and the other task might involve categorizing targets as smaller or larger than 5, with the relevant task indicated by a cue (e.g., *odd–even* or *small–large*). When task categories are mapped to the same manual response keys (e.g., odd and small mapped to a left key; even and large mapped to a right key), targets differ in their response congruency. Congruent targets are those for which the relevant and irrelevant task responses are the same (e.g., *3* is odd and small, requiring a left keypress response for both tasks). Incongruent targets are those for which the relevant and irrelevant task responses are different (e.g., *7* is odd and large, requiring a left keypress response for the odd–even task but a right keypress response for the small–large task).

A reliable finding in task-switching studies is a response congruency effect: response time (RT) is longer and error rate is higher for

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incongruent targets than for congruent targets (e.g., Brown et al., 2007; Kiesel, Wendt, & Peters, 2007; Meiran & Kessler, 2008; Monsell, Sumner, & Waters, 2003; Schneider, in press; Schneider & Logan, 2009, 2014; Sudevan & Taylor, 1987). Response congruency effects are hypothesized to reflect either a mediated or a nonmediated route for response selection, or both (Kiesel et al., 2007; Meiran & Kessler, 2008; Schneider, in press; Schneider & Logan, 2009, 2014; Yamaguchi & Proctor, 2011).

The mediated route involves categorizing the target with respect to both tasks, then selecting a response based on the instructed category–response mappings and the relevant task cue. The route is considered to be mediated because the pathway from target to response involves an intermediate category representation (e.g., *3* → odd → left key). For a congruent target (e.g., *3*), response selection is facilitated because both target categorizations (*3* is odd and small) are mapped to the same response (e.g., odd and small → left key). For an incongruent target (e.g., *7*), response selection is impaired because the target categorizations (*7* is odd and large) are mapped to different responses (e.g., odd → left key; large → right key), making it necessary to use the task cue to determine the appropriate categorization and response. It is in this way that the mediated route explains response congruency effects.

The nonmediated route involves bypassing categorization and using the target to directly retrieve an associated response from long-term memory based on target–response instances accumulated from past experience (Logan, 1988). The route is considered to be nonmediated because the pathway from target to response does not involve an intermediate category representation (e.g., *3* → left key). For a congruent target (e.g., *3*), response selection is facilitated because the target has been associated with the same response for each task in the past (e.g., *3* → left key for both the odd–even and small–large tasks). For an incongruent target (e.g., *7*), response selection is impaired because the target has been associated with different responses for each task in the past (e.g., *7* → left key for the odd–even task; *7* → right key for the small–large task), making it necessary to use the task cue to determine the appropriate response. It is in this way that the nonmediated route explains response congruency effects.

There is experimental evidence that both the mediated and nonmediated routes can contribute to response congruency effects in task-switching performance. The strongest evidence in favor of the mediated route is the finding of response congruency effects with nonrepeated targets, for which the nonmediated route is nonfunctional because there are no target–response instances to retrieve from long-term memory, thereby making categorization via the mediated route the sole mechanism available for response selection (Schneider, in press). Related evidence for the mediated route includes findings of response congruency effects with unpracticed target–response mappings (Liefooghe, Wenke, & De Houwer, 2012) and with irrelevant distractors that are never presented as targets (Reisenauer & Dreisbach, 2013). The strongest evidence in favor of the nonmediated route is the finding of inverted response congruency effects when category–response mappings are reversed, which implies response selection by using targets to directly retrieve responses from memory via the nonmediated route (Waszak, Pfister, & Kiesel, 2013; Wendt & Kiesel, 2008). Even though both routes can play roles in response selection, the mediated route is of particular interest in the present study because it is instantiated in the model of compound cue retrieval.

1.2. Compound cue retrieval

The core idea behind compound cue retrieval is that the task cue and target are categorized and used together to select a response from long-term memory. The target is categorized with respect to all tasks while the cue indicates the most relevant categorization. The combined category evidence from the cue and the target is used to drive a response-selection process based on the instructed category–response mappings. In its present form, the model does not learn or use any direct associations between targets and responses.[1] Consequently, response selection is based on categorization without access to target–response associations, which means that the model instantiates a form of the mediated route rather than the nonmediated route. The model and its equations are described in greater detail elsewhere (Schneider & Logan, 2005, 2009), so I will provide a condensed explanation of its functioning here.

The process starts with encoding of the cue and the target presented on a trial, resulting in semantic representations that provide evidence for task-relevant categories (Arrington, Logan, & Schneider, 2007; Schneider & Logan, 2010) as opposed to direct evidence for specific responses. Evidence is represented by η values and the evidence for each category is the product of the evidence from the cue and the target:

$$\eta_{\text{category}} = \eta_{\text{cue}} \times \eta_{\text{target}} \tag{1}$$

When a cue or a target is associated with a category, it provides associated evidence (η_a). When a cue or a target is not associated with a category, it provides unassociated evidence (η_u). It is assumed that evidence from associated stimuli is stronger than evidence from unassociated stimuli ($\eta_a > \eta_u$). For example, consider the odd–even and small–large tasks described earlier, and assume a trial on which the cue is *odd–even* and the target is *3*. The cue would provide associated evidence for the odd and even categories ($\eta_{\text{cue}} = \eta_a$) and unassociated evidence for the small and large categories ($\eta_{\text{cue}} = \eta_u$). The target would provide associated evidence for the odd and small categories ($\eta_{\text{target}} = \eta_a$) and unassociated evidence for the even and large categories ($\eta_{\text{target}} = \eta_u$). According to Eq. 1, the product of cue and target evidence would be largest for the odd category ($\eta_{\text{odd}} = \eta_a \times \eta_a$) and smallest for the large category ($\eta_{\text{large}} = \eta_u \times \eta_u$).

The probability of retrieving a given category from long-term memory is the ratio of its evidence over the sum of the evidence for all categories:

$$p_{\text{category}} = \eta_{\text{category}} \Big/ \sum \eta_{\text{category}} \tag{2}$$

When multiple categories are mapped to each response key, the probability of retrieving a given response is the sum of the category probabilities mapped to it:

$$p_{\text{response}} = \sum p_{\text{category}}, \text{ for category} \in \text{response} \tag{3}$$

The response probabilities represent the rates at which evidence accumulates for the responses during a random-walk decision process (Nosofsky & Palmeri, 1997). The random walk accumulates evidence at discrete time steps until the difference in evidence between responses reaches a criterion *C*, at which point the response with more evidence has been selected. The mean time per step and the mean number of steps for the random walk to finish are given by the following equations adapted from Nosofsky and Palmeri (1997) by Schneider and Logan (2005):

$$t_{\text{step}} = 1 \Big/ \sum \eta_{\text{category}} \tag{4}$$

and

$$n_{\text{step}} = \frac{1}{p_{\text{correct}} - p_{\text{error}}} [(\theta_1)(2C) - (\theta_2)(C)], \tag{5}$$

[1] A common misconception about the model is that the cue and the target form a compound stimulus that is associated directly with a response. In reality, cue and target representations remain separated in the model (e.g., see Schneider & Logan, 2005, p. 349), with the "compound" in "compound cue retrieval" referring to the fact that response selection involves a multiplicative (rather than additive) combination of category evidence from the cue and the target.

respectively, where

$$\theta_1 = \frac{(p_{\text{correct}}/p_{\text{error}})^{2C} + 1}{(p_{\text{correct}}/p_{\text{error}})^{2C} - 1} \tag{6a}$$

and

$$\theta_2 = \frac{(p_{\text{correct}}/p_{\text{error}})^{C} + 1}{(p_{\text{correct}}/p_{\text{error}})^{C} - 1}, \tag{6b}$$

and p_{correct} and p_{error} are the probabilities for correct and error responses, respectively. The mean time it takes for the random walk to finish selecting a response is the product of the time per step and the number of steps:

$$t_{\text{walk}} = t_{\text{step}} \times n_{\text{step}} \tag{7}$$

The model's prediction for mean RT is the sum of the random-walk time and a base time value that represents the time required by all nondecision processes, such as stimulus encoding and response execution:

$$\text{RT} = t_{\text{walk}} + t_{\text{base}} \tag{8}$$

The model's prediction for mean error rate is given by the following equation:

$$\text{Error rate} = 1 - \frac{1-(p_{\text{error}}/p_{\text{correct}})^{C}}{1-(p_{\text{error}}/p_{\text{correct}})^{2C}} \tag{9}$$

Eqs. 1–9 represent the basic model of compound cue retrieval. In the original model (Schneider & Logan, 2005), compound cue retrieval was combined with priming of cue encoding to account for task-transition effects. Logan and Bundesen (2003) and Mayr and Kliegl (2003) had noted that task transitions were confounded with cue transitions in experiments with one cue per task (i.e., task switches always involved cue switches and task repetitions always involved cue repetitions). When task and cue transitions were disentangled by using two cues per task, they found that a substantial portion of the so-called task-switch cost in performance reflected a cue-repetition benefit (see also Logan & Schneider, 2006; Monsell & Mizon, 2006; Schneider & Logan, 2006, 2011). To account for cue-repetition effects, Schneider and Logan (2005) assumed that repeated cues were encoded faster than nonrepeated cues, with cue encoding times represented by free parameters. When cue encoding time cannot be estimated separately from the base time for nondecision processes, as in the present study, different base times are estimated for task/cue switches and repetitions ($t_{\text{base–TCS}}$ and $t_{\text{base–TCR}}$, respectively). Schneider and Logan (2005) also assumed that repeated cues provide stronger evidence for associated categories in compound cue retrieval than do nonrepeated cues, which is implemented by allowing a separate η value for repeated cues (η_{r}, where $\eta_{\text{r}} > \eta_{\text{a}} > \eta_{\text{u}}$). These assumptions related to priming of cue encoding are relevant for the model fit presented later.

Schneider and Logan (2009) demonstrated that the model produces response congruency effects for both RT and error rate in task-switching situations involving two tasks. The model produces the effects because of how category evidence is mapped to responses differently on incongruent and congruent trials (numerical examples are provided in Schneider & Logan, 2014). For an incongruent trial, the two target categories provide associated evidence for different responses, generating ambiguity in response selection. The associated evidence from the cue for the relevant task categories resolves this ambiguity and enables a correct response to be selected, albeit after a long and error-prone random walk. For a congruent trial, the two target categories provide associated evidence for the same response, generating consistency in response selection. The associated evidence from the cue for the relevant task categories is redundant because the evidence from the target is sufficient for selecting a correct response, resulting in a short and accurate random walk. Thus, the model is slower and less accurate on incongruent trials than on congruent trials, producing response congruency effects.

As noted earlier, there is a variety of evidence from studies involving nonrepeated targets (Schneider, in press), unpracticed target–response mappings (Liefooghe et al., 2012), and irrelevant distractors that are never presented as targets (Reisenauer & Dreisbach, 2013) indicating that the mediated route can produce response congruency effects by itself. The model of compound cue retrieval provides a mechanistic account of the mediated route by demonstrating how response selection based on categorization can lead to different RTs and error rates for incongruent and congruent targets. In addition, the model has been shown to provide good quantitative fits to empirical response congruency effects in previous studies (Schneider & Logan, 2009, 2014), suggesting that its implementation of the mediated route is tenable.

1.3. A prediction

Compound cue retrieval has been applied previously to task-switching situations involving only two tasks (Logan & Schneider, 2010; Schneider & Logan, 2005, 2009, 2014). In my exploration of the model, I discovered that it makes a prediction about response congruency effects for situations involving three tasks. To provide context for the prediction, consider the odd–even and small–large tasks described earlier for single-digit targets, plus a near–far task that involves categorizing targets as near (*3*, *4*, *6*, *7*) or far (*1*, *2*, *8*, *9*) from 5 in terms of their numerical distance. Assume that the odd, small, and near categories are mapped to a left response key, and the even, large, and far categories are mapped to a right response key. Consider a trial on which the odd–even task is cued and an odd target is presented, resulting in the correct response being the left key. In this situation, there are three different types of response congruency based on the mapping of noncued target categories to responses:

- Incongruent (e.g., target is *9*): Both of the noncued target categories (large and far) are associated with the incorrect response.
- Congruent (e.g., target is *3*): Both of the noncued target categories (small and near) are associated with the correct response.
- Mixed (e.g., target is *1*): One of the noncued target categories (small) is associated with the correct response, whereas the other (far) is associated with the incorrect response.

The congruent and incongruent conditions for three tasks are analogous to their counterparts for two tasks because the noncued target categories are mapped exclusively to either the correct or incorrect response, respectively. The mixed condition is unique to the three-task situation because the noncued target categories are mapped to separate responses.

Response congruency effects have not been routinely reported for experiments involving three tasks. Arbuthnott (2005, Experiment 2) examined response congruency in a task-switching experiment involving three numerical categorization tasks, but she compared only incongruent and congruent trials, finding a response congruency effect on RT that was not modulated by task transition. The RT data for mixed trials and the error data for all trials were not reported in her analysis of response congruency. While a revision of this article was under review, Longman, Lavric, Munteanu, and Monsell (2014) published an eye-tracking study in which response congruency data were reported for two task-switching experiments that also involved three numerical categorization tasks. Except for a small reversal in the RTs for congruent and mixed trials in their Experiment 1, performance was worst for incongruent trials, intermediate for mixed trials, and best for congruent trials. The response congruency effects were not modulated by task transition. Thus, there is some preliminary evidence indicating that graded response congruency effects emerge when switching between three tasks.

The recent findings from Longman et al. (2014) seem inconsistent with the nonmediated route for response selection. If the nonmediated route is mainly responsible for response congruency effects, then one might predict similar performance for mixed and incongruent trials, with better performance for congruent trials. This prediction is based on the fact that mixed and incongruent trials both involve varied mappings of targets to responses, which would result in heterogeneous sets of target–response instances in long-term memory (i.e., the same target would be associated with different responses). This heterogeneity would impede direct retrieval of an unambiguous response in both conditions, resulting in impaired performance that would require using the task cue to resolve the ambiguity. In contrast, congruent trials involve consistent mappings of targets to responses, which would result in a homogeneous set of target–response instances in long-term memory (i.e., each target would always be associated with the same response). This homogeneity would enable direct retrieval of an unambiguous response, resulting in fast and accurate performance. Thus, the nonmediated route would predict the following pattern of performance: incongruent = mixed > congruent.

If the mediated route is mainly responsible for response congruency effects, then mixed-trial performance would depend on how alternative target categorizations are combined during response selection. Given that the model of compound cue retrieval implements the mediated route, it can be used to derive a prediction for mixed-trial performance. Even though the model has not been applied previously to a three-task situation, the logic is straightforward. The cue provides associated evidence for the two categories of the cued task (e.g., an *odd–even* cue provides associated evidence for the odd and even categories). The target provides associated evidence for one category of each of the three tasks (e.g., the target *3* provides associated evidence for the odd, small, and near categories). Each stimulus provides unassociated evidence for the remaining categories. Using Eq. 1, cue and target evidence are multiplied to produce the joint evidence for each of the six categories (odd, even, small, large, near, and far). Using Eq. 2, category evidence is translated into category probabilities. Using Eq. 3, the probabilities of the three categories mapped to a response are summed to produce the response probability. Eqs. 4–9 are used as described earlier.

I derived quantitative predictions from the model for incongruent, mixed, and congruent trials, assuming a task/cue switch and using a sample set of parameter values: $\eta_u = .01$, $\eta_a = .10$, and $C = 2.00$.[2] Table 1 shows the results of the model calculations for each trial type. The key results are the response probabilities calculated using Eq. 3: The difference between correct and error response probabilities progressively increases from incongruent to mixed to congruent trials. A larger difference translates into a more efficient random walk that takes fewer steps to select a response and is more likely to select the correct response. Consequently, the time for the random walk to finish gets shorter and its error rate decreases going from incongruent to mixed to congruent trials (see the two bottom rows of Table 1). In other words, the model – and, by extension, the mediated route – predicts graded response congruency effects on both RT and error rate, with the following pattern of performance: incongruent > mixed > congruent. This prediction is consistent with the general pattern reported by Longman et al. (2014).

The prediction was derived from the basic model of compound cue retrieval developed by Schneider and Logan (2005, 2009), applied without modification to a three-task situation for the first time. It is not obvious that other task-switching models make the same prediction. For example, Sohn and Anderson's (2001) model does not seem to predict response congruency effects at all because it implements only half of the mediated route, with the target categorized only with respect to the relevant task. Altmann and Gray's (2008) model does not predict response congruency effects from its core mechanisms, but it can produce them with a variant of the nonmediated route that leads to direct priming of responses by congruent targets. However, it does not appear to form target–response associations for incongruent targets, making it unclear whether the model would predict any difference between incongruent and mixed trials. Brown et al.'s (2007) model predicts response congruency effects via incongruency detection units that modulate the activity of task-set representations in a multilayer connectionist network, but it is unclear whether the model would distinguish between incongruent and mixed trials because both would activate the incongruency detectors. Gilbert and Shallice's (2002) connectionist model predicts Stroop effects that are analogous to response congruency effects, even producing color-naming RTs for neutral trials (e.g., naming the ink color of the letter string "xxxxx") that are between those of incongruent and congruent trials. Neutral trials are not analogous to mixed trials because they afford only one task, but it is possible that the model would predict intermediate performance for mixed trials, too. Simulation of the model would be needed to generate a prediction for mixed trials and to determine the specificity of the prediction (i.e., the model might be flexible enough to make a variety of predictions about mixed-trial performance). Overall, it seems as though Schneider and Logan's model of compound cue retrieval is one of the only models expressly in the task-switching domain that naturally and unequivocally predicts graded response congruency effects on both RT and error rate.[3]

I conducted an experiment to test this model prediction and independently replicate the relevant results of Longman et al. (2014). The experiment involved the aforementioned odd–even, small–large, and near–far tasks for single-digit targets. Tasks were cued in random order and each task was performed equally often. Targets were presented in random order and each target occurred equally often with each task. There were several methodological differences between Longman et al.'s experiments and the present experiment. First, tasks were associated with different spatial locations in Longman et al.'s experiments, necessitating reorientation of spatial attention across trials, whereas all tasks were associated with the same spatial location in the present experiment. Second, three different targets were displayed in separate spatial locations on each trial in Longman et al.'s experiments, whereas a single target was displayed on each trial in the present experiment. Third, there were two cues per task (neither of which indicated the category–response mappings), the cue was visible for only 100 ms, and the cue was presented before the target in Longman et al.'s experiments, whereas there was one cue per task (which indicated the category–response mappings), the cue was visible until a response was made, and the cue was presented simultaneously with the target in the present experiment. Fourth, there were 24 subjects in the critical condition in each of Longman et al.'s experiments, whereas there were 80 subjects in the present experiment to improve statistical power. Given these methodological differences, the question of interest was whether the graded response congruency effects reported by Longman et al. and predicted by the model would be observed.

2. Method

2.1. Subjects

Eighty students from Purdue University participated for course credit. Data from five additional subjects were excluded for mean error rates exceeding a preset inclusion criterion of 20%. Three of the excluded

[2] The same pattern of results is obtained if a task/cue repetition is assumed or if other sets of reasonable parameter values are used.

[3] It is possible that models of compatibility effects outside of the task-switching domain (e.g., Cohen, Dunbar, & McClelland, 1990; Yamaguchi & Proctor, 2012) could be adapted to the present experimental context to make the same prediction as the model of compound cue retrieval. However, it is unclear whether those models would be able to accommodate the other task-switching phenomena explained by compound cue retrieval (see Logan & Schneider, 2010; Schneider & Logan, 2005, 2009, 2014).

Table 1
Sample model predictions for response selection involving three tasks.

Model attribute	Response congruency		
	Incongruent (target = *9*)	Mixed (target = *1*)	Congruent (target = *3*)
Category evidence (Eq. 1)			
η_{odd}	.0100	.0100	.0100
η_{even}	.0010	.0010	.0010
η_{small}	.0001	.0010	.0010
η_{large}	.0010	.0001	.0001
η_{near}	.0001	.0001	.0010
η_{far}	.0010	.0010	.0001
$\Sigma\eta$	.0132	.0132	.0132
Category probabilities (Eq. 2)			
p_{odd}	.7576	.7576	.7576
p_{even}	.0758	.0758	.0758
p_{small}	.0076	.0758	.0758
p_{large}	.0758	.0076	.0076
p_{near}	.0076	.0076	.0758
p_{far}	.0758	.0758	.0076
Response probabilities (Eq. 3)			
$p_{correct}$ ($p_{odd} + p_{small} + p_{near}$)	.7727	.8409	.9091
p_{error} ($p_{even} + p_{large} + p_{far}$)	.2273	.1591	.0909
Random walk steps (Eqs. 4–6a and 6b)			
t_{step}	75.76	75.76	75.76
n_{step}	3.1	2.7	2.4
Predictions (Eqs. 7 and 9)			
t_{walk}	234	207	182
Error rate	8.0	3.5	1.0

Note. The predictions are for scenarios in which the odd–even task is cued; the target is odd; the odd, small, and near categories are mapped to the same response (e.g., a left key); and the even, large, and far categories are mapped to the same response (e.g., a right key). The predictions generalize to the other tasks, targets, and category–response mappings under consideration.

subjects appeared to have reversed the category–response mappings for at least one task, indicating a failure to follow instructions.

2.2. Apparatus, tasks, stimuli, and responses

The experiment was conducted on computers that displayed stimuli on monitors and registered responses from QWERTY keyboards. Stimuli were displayed in white 18-point Courier New font on a black background at a viewing distance of approximately 50 cm.

Three numerical categorization tasks were performed on the single-digit targets *1*–*9*, excluding *5*. The odd–even task, cued by the words *odd–even*, involved categorizing a target as odd or even. The small–large task, cued by the words *small–large*, involved categorizing a target as smaller or larger than 5. The near–far task, cued by the words *near–far*, involved categorizing a target as near (*3*, *4*, *6*, *7*) or far (*1*, *2*, *8*, *9*) from 5 in terms of its numerical distance. The instructions indicated which targets belonged in each category for all tasks.

Responses were made with the D and K keys on the keyboard, with same-task categories mapped to different keys (e.g., odd, small, and near categories mapped to the D key; even, large, and far categories mapped to the K key). The eight possible sets of category–response mappings were counterbalanced across subjects. The left–right order of the category words composing the cues matched the left–right order of the response keys for each subject (e.g., a subject with far and near categories mapped to the D and K keys, respectively, had *far–near* as a cue).

The category–response mappings defined the response congruency of the targets. For example, consider a subject with odd, small, and near categories mapped to the D key, and even, large, and far categories mapped to the K key. Assume that the odd–even task is cued and an odd target is presented, resulting in the correct response being the D key. An example of an incongruent target would be *9*, for which both of the noncued categorizations (large and far) are associated with the incorrect response (K key). An example of a mixed target would be *1*, for which one of the noncued categorizations (small) is associated with the correct response (D key) but the other noncued categorization (far) is associated with the incorrect response (K key). An example of a congruent target would be *3*, for which both of the noncued categorizations (small and near) are associated with the correct response (D key). Due to the counterbalancing of category–response mappings, the response congruency of a given target differed across subjects.

2.3. Procedure

Subjects were seated at computers in individual testing rooms after providing informed consent for a study protocol approved by the Purdue University Institutional Review Board. Instructions were presented onscreen and read aloud by the experimenter.

The experiment was divided into 8 blocks of 48 trials, with self-paced rest periods between blocks. Each trial began with two vertically arranged fixation crosses presented in the center of the screen. After 500 ms, the top and the bottom fixation crosses were replaced simultaneously by a cue and a target, respectively. Cue and target remained onscreen until the subject responded, then the screen was blank for 500 ms before the next trial commenced.

The cue and the target were selected randomly on each trial, subject to the constraint that each task was performed equally often and each target occurred equally often with each task in every block. Due to the random selection of cues, task switches (e.g., the odd–even task followed by the small–large task) and task repetitions (e.g., the odd–even task followed by the odd–even task) occurred randomly across trials. Due to the random selection of targets, 25% of the targets in each block were incongruent, 25% were congruent, and 50% were mixed.

Table 2
Mean correct response time and mean error rate as a function of task transition and response congruency (with model predictions in parentheses).

Measure	Task transition	Response congruency		
		Incongruent	Mixed	Congruent
Response time	Task switch	1449 (1450)	1432 (1430)	1405 (1406)
	Task repetition	1181 (1177)	1155 (1162)	1147 (1144)
Error rate	Task switch	5.6 (5.8)	3.8 (3.5)	2.3 (1.5)
	Task repetition	4.6 (5.1)	3.2 (3.2)	2.3 (1.5)

3. Results

3.1. Data analysis

The first block was treated as practice and excluded from analysis. The first trial of each subsequent block was excluded because it lacked an immediately preceding trial for classifying the task transition. Trials with RTs more than three standard deviations above the mean in each condition for a given subject were excluded (2.0% of trials). Error trials were excluded from the RT analysis. Mean correct RT and mean error rate were calculated for each subject in each condition of the 3 (response congruency: incongruent, mixed, or congruent) × 2 (task transition: task switch or task repetition) experimental design and submitted to separate repeated-measures ANOVAs with those variables as factors. Means for all conditions are provided in Table 2.

Mean correct RTs are presented as bars in Fig. 1A. RT became progressively shorter going from incongruent (1315 ms) to mixed (1293 ms) to congruent (1276 ms) trials, resulting in a significant main effect of response congruency, $F(2,158) = 4.79$, MSE = 12735.15, $p = .01$, $\eta_p^2 = .06$, consistent with the general pattern reported by Longman et al. (2014). Two orthogonal contrasts were used to analyze the form of the response congruency effect. The first contrast tested for a linear trend and was significant, $F(1,158) = 9.51$, MSE = 12735.15, $p = .002$, $\eta_p^2 = .06$. The second contrast tested whether mixed-trial RT differed from the mean of the incongruent- and congruent-trial RTs. This contrast was nonsignificant, $F(1,158) = 0.04$, MSE = 12735.15, $p = .84$, $\eta_p^2 < .01$, indicating that mixed-trial RT was not reliably closer to either incongruent- or congruent-trial RT.[4] Task switches (1429 ms) were slower than task repetitions (1161 ms), resulting in a significant main effect of task transition, $F(1,79) = 215.97$, MSE = 39794.27, $p < .001$, $\eta_p^2 = .73$. The interaction between response congruency and task transition was nonsignificant, $F(2,158) = 0.34$, MSE = 10881.52, $p = .72$, $\eta_p^2 < .01$, consistent with null interactions reported by Arbuthnott (2005) and Longman et al.

Mean error rates are presented as bars in Fig. 1B. Error rate decreased going from incongruent (5.1%) to mixed (3.5%) to congruent (2.3%) trials, resulting in a significant main effect of response congruency, $F(2,158) = 21.19$, MSE = 15.26, $p < .001$, $\eta_p^2 = .21$, consistent with the general pattern reported by Longman et al. (2014). Two orthogonal contrasts were used to analyze the form of the response congruency effect. The first contrast tested for a linear trend and was significant, $F(1,158) = 41.94$, MSE = 15.26, $p < .001$, $\eta_p^2 = .21$. The second contrast tested whether mixed-trial error rate differed from the mean of the incongruent- and congruent-trial error rates. This contrast was nonsignificant, $F(1,158) = 0.40$, MSE = 15.26, $p = .53$, $\eta_p^2 < .01$, indicating that mixed-trial error rate was not reliably closer to either incongruent- or congruent-trial error rate. Task switches (3.9%) elicited more errors than did task repetitions (3.4%), resulting in a significant main effect of task transition, $F(1,79) = 4.67$, MSE = 8.02, $p = .03$, $\eta_p^2 = .06$. The interaction between response congruency and task transition was nonsignificant, $F(2,158) = 1.26$, MSE = 8.06, $p = .29$, $\eta_p^2 = .02$, consistent with null interactions reported by Longman et al.

The data were also analyzed with respect to lag-2 task-transition effects. When switching between three tasks (denoted A, B, and C), performance is sometimes worse for lag-2 task repetitions (e.g., ABA) than for lag-2 task switches (e.g., CBA), an effect routinely attributed to task-set inhibition (Mayr & Keele, 2000; for a review, see Koch, Gade, Schuch, & Philipp, 2010). After excluding the first two trials of each block and including only those trials preceded by two correct trials, the RT and error data were submitted to separate 3 (response congruency: incongruent, mixed, or congruent) × 2 (lag-2 task transition: lag-2 task switch or lag-2 task repetition) repeated-measures ANOVAs. To avoid redundancy with the previous analyses, only effects involving lag-2 task transition are reported.

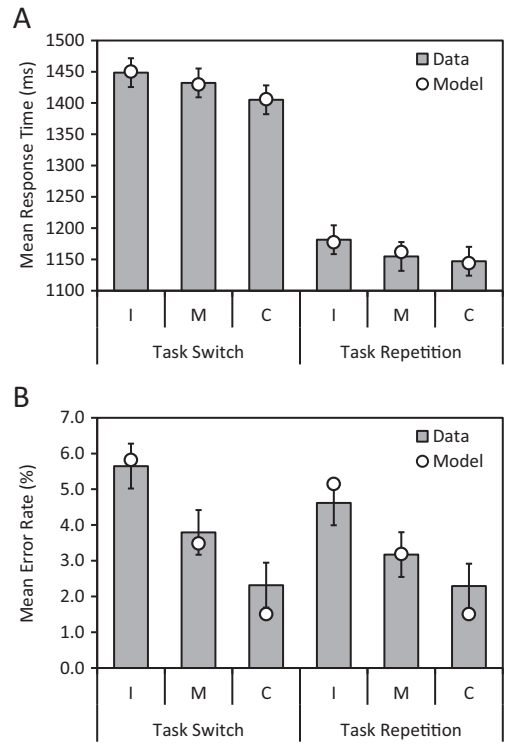

Fig. 1. Mean correct response time and mean error rate as a function of task transition and response congruency (I = incongruent, M = mixed, C = congruent). Error bars represent 95% confidence intervals (Masson & Loftus, 2003).

RT was nearly identical for lag-2 task repetitions (1341 ms) and for lag-2 task switches (1342 ms), resulting in a nonsignificant main effect of lag-2 task transition, $F(1,79) = 0.01$, MSE = 13614.77, $p = .92$, $\eta_p^2 < .01$. Interestingly, Longman et al. (2014) found a significant 14-ms lag-2 task-repetition benefit in their Experiment 1 and a nonsignificant 3-ms lag-2 task-repetition cost in their Experiment 2, suggesting that lag-2 task-transition effects are neither large nor robust with numerical categorization tasks. The interaction between response congruency and lag-2 task transition was nonsignificant in the present data, $F(2,158) = 0.48$, MSE = 15113.91, $p = .62$, $\eta_p^2 < .01$, consistent with a null interaction reported by Arbuthnott (2005, Experiment 2).

Error rate was numerically but not reliably higher for lag-2 task repetitions (4.3%) than for lag-2 task switches (3.8%), resulting in a nonsignificant main effect of lag-2 task transition, $F(1,79) = 1.70$, MSE = 14.23, $p = .20$, $\eta_p^2 = .02$. Longman et al. found a significant 0.5% lag-2 task-repetition cost in their Experiment 1 and a nonsignificant 0.04% lag-2 task-repetition cost in their Experiment 2, suggesting that lag-2 task-repetition effects are weak for both RT and error rate with numerical categorization tasks. However, the interaction between response congruency and lag-2 task transition was significant in the present data, $F(2,158) = 4.85$, MSE = 22.49, $p = .009$, $\eta_p^2 = .06$. For lag-2 task repetitions, mixed-trial error rate (3.5%) was closer to congruent-trial error rate (2.1%) than to incongruent-trial error rate (7.2%), whereas for lag-2 task switches, mixed-trial error rate (4.6%) was closer to incongruent-trial error rate (5.0%) than to congruent-trial error rate (1.8%).

[4] To investigate the stability of the response congruency effect across the RT distribution, cumulative distribution functions were computed for incongruent, mixed, and congruent trials for each subject. The data were submitted to a 3 (response congruency: incongruent, mixed, or congruent) × 5 (quantile: .1, .3, .5, .7, or .9) repeated-measures ANOVA that revealed a nonsignificant interaction, $F(8,632) = 0.52$, $MSE = 10231.60$, $p = .84$, $\eta_p^2 < .01$, indicating no reliable modulation of the response congruency effect (for similar results, see Schneider, in press, Experiments 1 and 2).

3.2. Modeling analysis

The model of compound cue retrieval described by Eqs. 1–9 and including the aforementioned assumptions about priming of cue encoding was fit simultaneously to the aggregate RT and error data shown in Table 2 (a total of 12 data points). There were five free parameters (η_u, η_a, η_r, C, and $t_{base-TCS}$) that were constrained such that the values of η_u, η_a, and η_r could not be smaller than .001 and the value of C could not be smaller than 1. Preliminary model fits involving different sets of starting parameter values revealed that the sixth and final model parameter, $t_{base-TCR}$, could be fixed at a reasonable value without impairing the fit because the values of the other five parameters could change to compensate, so it was set equal to 500 ms. The Solver routine in Microsoft Excel optimized parameter values to minimize the sum of the root mean squared deviations (RMSDs) for RT and error rate. The correlation (r) between data and model was also calculated for each dependent measure.

The best-fitting model predictions are displayed in parentheses in Table 2 and plotted as points in Fig. 1. The model reproduced the empirical pattern of graded response congruency effects on both RT and error rate, with nearly all of its predictions falling within the 95% confidence intervals of the data (see Fig. 1). In addition, the model reproduced the empirical pattern of task-transition effects on both RT and error rate. The fit indices for RT (RMSD = 3.7 ms, $r > .999$) and error rate (RMSD = 0.5%, $r = .986$) indicate a quantitatively close fit between model and data. The best-fitting parameter values were $\eta_u = .002$, $\eta_a = .040$, $\eta_r = .047$, $C = 1.273$, and $t_{base-TCS} = 660$ ms.

No attempt was made to model lag-2 task-transition effects because there was not a reliable lag-2 task-repetition cost for either RT or error rate in the present data. Moreover, Longman et al. (2014) reported mixed results concerning lag-2 task-transition effects, making it unclear whether such effects are robust with numerical categorization tasks. It is worth noting that the model of compound cue retrieval – in its present form – does not predict any lag-2 task-transition effects, but it is not alone in this regard. I am aware of only one published task-switching model that can produce lag-2 task-repetition costs (Grange, Juvina, & Houghton, 2013), but that model does not produce response congruency effects.

4. Discussion

The purpose of the present study was to test a prediction derived from a model of response selection in task-switching situations. Schneider and Logan's (2005, 2009) model of compound cue retrieval, which implements a mediated route for response selection, predicts graded response congruency effects for incongruent, mixed, and congruent trials when switching between three tasks. This prediction was tested in an experiment involving numerical categorization tasks performed on single-digit targets. The experimental results revealed a progressive shortening of RT and decrease in error rate going from incongruent to mixed to congruent trials (see Fig. 1), which is consistent with the prediction of the mediated route represented by the model, as well as results reported by Longman et al. (2014). In the remainder of this article, I discuss the implications of the present study for understanding response congruency effects and for developing models of task-switching performance.

A notable aspect of the data is that the response congruency effect was unaffected by whether a trial involved an immediate task switch or task repetition. Null interactions between response congruency and task transition have been reported in previous studies (e.g., Longman et al., 2014; Meiran, 1996; Meiran, Chorev, & Sapir, 2000; Monsell et al., 2003; Schneider, in press; but see Goschke, 2000; Monsell & Mizon, 2006), suggesting that the locus of response congruency effects in the cognitive processing stream might be separate from and later than the locus of task-transition effects. This suggestion is largely consistent with how the effects were treated in Schneider and Logan (2005), where the original formal model of compound cue retrieval was presented. They argued that task-transition effects could be attributed to priming of cue encoding (see also Logan & Schneider, 2006; Schneider & Logan, 2006), whereas response congruency effects could be attributed to compound cue retrieval (see Schneider & Logan, 2009). Given that cue encoding typically occurs before response selection in this version of the model (cf. Schneider & Logan, 2014), task switching would not be expected to strongly modulate response congruency effects, consistent with reports of null interactions.

The late locus of response selection might also explain why response congruency effects are not consistently modulated by other experimental manipulations. For example, even though task-transition effects (including those due to cue repetition) tend to diminish over longer cue–target intervals (e.g., Logan & Bundesen, 2003; Meiran, 1996; Monsell & Mizon, 2006), response congruency effects are less influenced by the length of the cue–target interval (e.g., Meiran, 2000; early sessions in Sudevan & Taylor, 1987; but see Meiran, 1996; Monsell & Mizon, 2006; late sessions in Sudevan & Taylor, 1987). As another example, response congruency effects are not influenced by working memory load, regardless of whether the load is manipulated by varying the number of task-irrelevant stimuli to be remembered (Kiesel et al., 2007) or the number of task-irrelevant category–response mappings in working memory (Kessler & Meiran, 2010). Based on additive-factors logic (Sternberg, 1969), these null interactions would be expected if response congruency were processed during a different stage (viz., response selection) than where task switching and other manipulations affect cognition.

The nature of the response congruency effect also provides insight into how the response selection stage operates in task-switching situations. As mentioned earlier, response congruency effects have been hypothesized to reflect mediated and nonmediated routes for response selection (Kiesel et al., 2007; Meiran & Kessler, 2008; Schneider, in press; Schneider & Logan, 2009, 2014; Yamaguchi & Proctor, 2011). Compound cue retrieval instantiates the mediated route because processing in the model involves the intermediate step of categorization. The cue provides associated evidence for the relevant task categories and the target provides associated evidence for multiple task categories. The joint category evidence from both stimuli is used to drive a random-walk decision process for selecting a response. The finding that compound cue retrieval predicted graded response congruency effects that were observed experimentally lends credence to the idea of a mediated route for response selection in task-switching situations.

However, the present study does not rule out a contribution of the nonmediated route to response congruency effects, and a few studies have provided evidence in its favor (e.g., Kiesel et al., 2007; Waszak et al., 2013; Wendt & Kiesel, 2008; Yamaguchi & Proctor, 2011). Recall that processing via the nonmediated route involves bypassing categorization and using the target to directly retrieve an associated response from long-term memory based on target–response instances accumulated from past experience (Logan, 1988). A congruent target would be associated with the same response regardless of the task performed, resulting in a homogeneous set of target–response instances that should facilitate response selection. Incongruent and mixed targets would be associated with different responses depending on the task performed, resulting in heterogeneous sets of target–response instances that should impair response selection. Consequently, I inferred a prediction based on the nonmediated route of similar performance for incongruent and mixed targets, and better performance for congruent targets. Even though the data were inconsistent with that prediction, it is possible that a version of the nonmediated route that is integrated with the mediated route would be more tenable.

If target–response instances were stored in long-term memory and retrieved by the nonmediated route, then two-thirds of instances would involve the incorrect response for an incongruent target and one-third of instances would involve the incorrect response for a mixed target, assuming tasks were performed equally often on each target, as in the present experiment. If response selection were sensitive to the relative proportion

of conflicting instances, then it is possible that the nonmediated route could yield slower and more error-prone performance for incongruent targets than for mixed targets. For example, consider a random-walk model that accumulates target–response instances rather than (or in addition to) category evidence from the cue and the target. If instances are retrieved at rates corresponding to their relative proportions in long-term memory, then instances associated with the correct response should accumulate fastest for congruent targets and slowest for incongruent targets, with accumulation for mixed targets occurring at an intermediate rate.

Such a model has the potential to produce graded response congruency effects, but it would need to be augmented further to enable accurate response selection on most trials. More specifically, if response selection were based solely on the retrieval of instances, then error rates would be extremely high for incongruent targets because the majority of instances would indicate the incorrect response. An instance-based model would need to use cue information to focus on the task-relevant response, counteracting the tendency to produce errors on incongruent trials. Following a suggestion of Schneider and Logan (2014), one approach might involve creating a dual-route model that integrates the mediated and nonmediated routes. Instances in favor of each response could accumulate via the nonmediated route while category evidence from the cue and the target could activate responses via the mediated route. By weighting the relative contributions of each route to response selection, this dual-route model might be flexible enough to accommodate results that have been attributed to either the mediated or the nonmediated route.

The last point draws attention to the importance of continuing to develop and test computational models of cognition, especially in the task-switching domain. At the start of this article, I lamented the fact that many task-switching models seem to be one-off efforts that have not been pursued beyond the original articles in which they were proposed, even by their own creators. My goal in the present study was to address this shortcoming by demonstrating how a prediction can be derived from an existing model and tested experimentally. As noted by Bjork (1973), some of the value of a mathematical or computational model lies in the ability to derive consequences from its assumptions that can potentially falsify it. Compound cue retrieval's prediction of graded response congruency effects for a three-task situation is an example of this point. The experimental results closely matched the model's prediction, but there was no guarantee of that happening. By predicting an effect that was subsequently observed, the model receives some validation that merits further exploration of the mediated route as an explanation of response congruency effects in task switching, though it does not rule out a contribution from the nonmediated route. Cumulative model development arises from continually challenging models to predict and explain more phenomena, revising and extending them as appropriate. I think that additional modeling efforts in this vein will pave the way toward a more comprehensive and integrated account of performance in task-switching situations.

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