

An Instance-Based Learning Model of Stimulus-Response Compatibility Effects in Mixed Location-Relevant and Location-Irrelevant Tasks

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Abstract

This paper presents a cognitive model of stimulus-response compatibility (SRC) effects for a situation in which location-relevant and location-irrelevant tasks are intermixed within a single trial block. We provide a computational explanation of the cognitive processing involved in the mixed-task condition. The model is based on the Instance-Based Learning Theory, developed originally to explain decision making in dynamic tasks, and the ACT-R theory of cognition. The comparison of the model's outputs to human data demonstrates high similarity, and the model offers an explanation for sequential modulations of the SRC/Simon effects observed when compatible and incompatible trials repeat or switch. Several possibilities to apply this model to novel tasks are discussed.

Keywords: Instance-Based Learning; ACT-R; Simon effect; Stimulus-response compatibility; Situation; Decision; Utility; Experience.

Introduction

In everyday activities, there are numerous situations where one is required to perform multiple tasks concurrently or in a sequence. The nature of performance is often altered in such a task condition, compared to that for a single task performed in isolation. Thus, studies of multi-task performance have been of major interest to basic and applied researchers. The main aim of the present research is to develop a computational model of human performance in a multi-task condition, in which task performance is known to be different from that for a single-task condition.

In choice-reaction tasks, responses are faster and more accurate when stimuli are mapped to spatially compatible responses than when they are mapped to spatially incompatible responses. The difference in response times and accuracy for the compatible and incompatible mappings is termed the *stimulus-response compatibility* (SRC) effect. SRC has been recognized as one of the critical principles for human interface design (Proctor & Vu, 2006) as well as a major motivation for theories of human perception and action (Hommel, Müsseler, Aschersleben, & Prinz, 2001).

The SRC effect is known to be so robust that it is obtained even when stimulus location is irrelevant to performing the task, the variation known as the *Simon Effect* (Simon, 1990). The robustness of the SRC/Simon effects has also been demonstrated using a variety of stimuli (Proctor, Yamaguchi, Zhang, & Vu, 2009), response modes (Wang, Proctor, & Pick, 2003), and more realistic tasks such as flight operations (Yamaguchi & Proctor, 2006).

However, the Simon effect can be reduced, eliminated, or even reversed when participants practice a choice-reaction task with the incompatible mapping prior to performing the Simon task (Proctor & Lu, 1999). Similarly, the Simon effect is attenuated when participants perform the Simon task concurrently with the SRC task (Marble & Proctor, 2000); that is, when location-irrelevant (the Simon task) and location-relevant (the SRC task) tasks are intermixed. The Simon effect increases somewhat when the SRC task requires a compatible mapping but reverses to a negative effect of at least the same absolute size when the SRC task requires an incompatible mapping.

A dominant cognitive explanation of the SRC/Simon effects is a *dual-route account* (Proctor & Vu, 2006), which assumes two distinct response-selection processes, characterized as direct and indirect routes. The indirect route is presumed to activate a response based on the intentions created through the instructed stimulus-response (S-R) mappings. In contrast, the direct route is presumed to automatically activate a response corresponding to the stimulus location, which facilitates responding when that response is correct but interferes when it is incorrect. However, given recent findings that the SRC/Simon effects can be attenuated in mixed-task conditions and after practice with an incompatible-mapping task, the response-selection process that gives rise to the SRC/Simon effects does not seem to be as purely automatic as it is typically described in the literature.

In contrast to the dual-route account, the present paper provides a computational model of the SRC/Simon effects developed based on the Instance-Based Learning Theory (IBLT; Gonzalez, Lerch & Lebiere, 2003). The goal of the current paper is to determine how the IBLT would predict the learning and performance obtained from an experiment

in which human subjects performed mixed Simon and SRC tasks.

We first provide a description of the task and the human data collection protocols, and then present the development of the IBLT model and the fits of the model predictions to human data. The paper concludes with examples of how the model can be used to generate predictions for novel task conditions.

Experiment on Mixed Simon/SRC Task

The task adopted here is similar to those used by Marble and Proctor (2000), in which participants performed mixed location-relevant and location-irrelevant tasks. Though their experiments separately examined the influences of the compatible and incompatible mappings on the Simon effect by individually mixing these mapping trials with the Simon task, the present experiment mixed both compatible- and incompatible-mapping trials with the Simon task.

Thirty-two undergraduate students at Purdue University participated in the experiment. They were recruited from the subject pool of introductory psychology courses and received partial course credits. All participants reported having normal or corrected-to-normal visual acuity, normal color vision, and normal hearing.

The experiment was conducted individually in a dimly lit cubicle and controlled by a custom application constructed by VisualBasic 6.0 (VB). The imperative stimuli were circles (5 mm in diameter) presented on the left or right side of the screen (6 cm from the center of the screen). The circles were colored in green, red, or white. Participants responded according to the color of the stimulus on some trials (the Simon trials) and to the location of the stimulus on other trials (the SRC trials). Green and red circles were used for the Simon trials, and a white circle was used for the SRC trials. Responses were made by pressing a left ('z') or right ('/') key on the computer keyboard.

On the Simon trials, a red circle required pressing of one response key, and a green circle required pressing of the other response key. The color-key mapping was counterbalanced across participants. The location of the circle was task-irrelevant.

On the SRC trials, a mapping cue, a horizontal or vertical line (5 mm in length) colored in white and centered on the screen, was presented simultaneously with the white circle. For half of the participants, a horizontal line required pressing a response key on the same side as the location of the circle (compatible-mapping trials), and a vertical line required pressing a response key located on the opposite side to the location of the circle (incompatible-mapping trials). For the other half, the cue-mapping relation was reversed.

Each trial started with a white fixation cross presented at the center of the screen for 500 ms, followed by a blank screen lasting for 500 ms. Then, a circle appeared on the left or right of the screen, with a horizontal or vertical line if it was an SRC trial. The circle was presented until a response was made or for 1,500 ms if no response was made. When

participants pressed an incorrect key, an error tone was presented from the external speakers positioned on the left and right of the screen. The frequency of the tone was 400 Hz, lasting for 500 ms. No feedback was given for a correct response but a blank display was presented for 500 ms. Thus, the inter-trial intervals for correct and incorrect responses were the same. A trial ended with a 1-s blank screen, and the next trial started with the fixation cross.

Response time and accuracy were recorded on each trial. Response time was the interval between onset of a circle and depression of a response key. Both speed and accuracy were emphasized in instructions. An experimental session lasted less than an hour.

Each participant performed four trial blocks. In each block, 80 trials were the Simon trials, and another 80 trials were the SRC trials (40 trials for the compatible mapping and 40 trials for the incompatible mappings). These trial conditions appeared equally often in each block in a random order.

An experimental session started with a block of practice trials. The practice block consisted of 16 Simon trials and 16 SRC trials (8 trials for each mapping). Participants were allowed to repeat the practice block as many times as they wanted, so that they were sufficiently familiar with the task requirements (no participants repeated more than 3 practice blocks). Results of this experiment are presented in a later section, where they are compared to the results of the IBLT computational model.

Development of the IBLT Model

We propose that IBLT provides reasonable cognitive explanations for the SRC and Simon effects. IBLT was originally developed as a way to explain and predict decision making in dynamic, complex tasks (Gonzalez, et al., 2003). The theory evolved from the idea that decisions are made from experience and that one could manipulate experience and therefore predict decisions made in the future.

IBLT proposes that people remember past experiences in terms of "instances." At each decision-making situation, an instance is retrieved and reused depending on the similarity of the current situation to the cues stored in the instance.

An instance is composed of three parts: situation, decision, and utility of that decision in that situation (situation-decision-utility or SDU triplet). In IBLT, decisions from experience involve five mental stages in a closed-loop decision making cycle: recognition, judgment, choice, execution, and feedback. Although IBLT the general decision process and particular mechanisms of decisions from experience are independent from the computational implementation of the theory, IBLT has borrowed many of the proposed mechanisms from the mathematical representations in ACT-R (Anderson et al., 2004).

ACT-R is an integrated computational cognitive architecture resulting from decades of cumulative effort by an international community of cognitive researchers, and it provides IBLT with the following advantages for a

computational implementation; (a) procedural and declarative memory modules, including both conscious and unconscious (i.e., statistical) reasoning and learning mechanisms, that have been validated by hundreds of laboratory experiments; (b) perceptual and motor modules that incorporate many known human-factors parameters and provide principled limitations in the interaction with an external learning environment; and (c) a method for assembling small, sub-second cognitive steps into computational models that can learn to perform increasingly complex dynamic tasks while interacting directly with information-processing systems and other human and synthetic agents. ACT-R has two levels of knowledge representation and manipulation; symbolic (knowledge representation) and subsymbolic (set of statistical and mathematical procedures to manipulate the symbolic level).

Symbolic level of the Simon/SRC model

For the current Simon/SRC task, the SDU instance (referred to as "chunk" in ACT-R) had the structure shown in Table 1. The first column defines the slot names of the instance while the second and third columns provide description of SDU slots. *Color* in Table 1 refers to the value of the color slot in the IBLT model, where it can contain the values red (R) and green (G) for the Simon trials and white (W) for the SRC trials. *Orient* is the value in the orientation slot, representing the orientation of the mapping cue used only for the SRC trials. Orient can contain horizontal (H) or vertical (V) for the SRC trials, and it is set at NO for the Simon trials where no mapping cue is used. *Position* slot provides the position of the imperative stimulus on the screen and can take only two values; left (Lt) and right (Rt). The *Decision* slot in Table 1 defines whether the decision is to press the left ('z') or right ('/') key on the computer keyboard to respond to the stimulus on the SRC and Simon trials. The *Utility* slot stores the utility of the decision, which is unknown at first and then updated after the IBLT model receives feedback from the task on its previous decision. The Utility slot can take three values; +1 (for correct decision), -1 (for incorrect decision), and 0 (unknown).

Table 1: SDU structure of Instance

Slot Name	Description	SDU
Color	Stimulus Color	Situation
Orient	Stimulus Orientation	Situation
Position	Stimulus Position	Situation
Decision	Key-press Decision	Decision
Utility	Utility of Decision	Utility
IBLT-State	State in IBLT Theory	Meta-Slot

In the above table, the *IBLT-State* (a Meta-Slot not used in IBLT model processing) could hold a value from any of the five process states of recognition, judgment, choice, execution, and feedback depending on the state of execution of the IBLT model on the Simon/SRC task. This slot only serves to distinguish the stage of IBLT modeling process.

As in Gonzalez et al. (2003), in IBLT the decision making starts with the recognition process in search for alternatives (the left or right keys) and the classification of the current situation as *typical* or *atypical*. The current situation is typical if there are memories of similar situations (i.e., instances of previous trials that are similar enough to the current situation). If it is typical, then the retrieved instance is used in judging the value of the decision to be made in the current situation. If the situation is atypical (i.e., no instance similar to the current conditions is found), a judgment heuristic is applied. Next, a decision point comes into place; whether to search for more alternatives or to execute the current best alternative. The answer to the choice is determined by the decision maker's "aspiration level," similar to Simon and March's (1958) satisficing strategy. In the Simon/SRC task, given their simplicity, the choice is simply made by making the same choice as the one in the decision slot of the retrieved instance (if nothing was retrieved, then a choice is made randomly for a key press, i.e., by a random judgment heuristic). After the execution of an action, if the response was incorrect, the SDU that led to the incorrect decision is modified by updating the Utility so as to provide a better representation of the "goodness" of that action.

The exact sequence of events in the IBLT Simon/SRC model is provided below. Each of the IBLT stages is represented by production rules (If-then rules) in ACT-R.

Recognition According to the similarity of a task situation and instances stored in memory, if there is a recognition (or retrieval) failure (as it is the case in the first trial, since there is no instances stored) the model applies a random judgment heuristic to select the type of action required by the task; else if there is a recognition (or retrieval) success the model applies an instance based judgment procedure.

Judgment When there is a recognition failure the model chooses a random number between 0 and 1 and if the number is greater than 0.5 then the right key is selected; else if it is less than or equal to 0.5 then the left key is selected. In case of recognition success, the model applies the decision of the instance that was retrieved successfully as the decision of the current instance. The model assigns the Utility slot of the current instance a value of unknown (i.e. 0) at this point.

Choice This refers to picking the selected key to press once the decision of retrieved instance or random heuristic has been made.

Execution At this step the model presses the selected key and waits for feedback for the action.

Feedback On obtaining the outcome of the decision just executed (error tone), the model updates the Utility of the current instance. If the decision made was correct it assigns Utility a value of +1; else if the decision made was not correct then it assigns Utility a value of -1.

In the above algorithm, the Utility slot is used at the time of retrieval (i.e., the recognition process) to divide the declarative memory (DM) into collections of correct and incorrect decision instances and confine the retrieval to only

those instances that have in the past yielded correct decision outcomes (i.e., their Utility slots have a value of +1).

Also, in the above algorithm, the productions were assumed to take an architectural default value of 50 ms (Anderson et al., 2004). There were some steps executed to read and encode the stimulus from the screen (visual time) and also to hear and encode the feedback tone of 400 Hz frequency (auditory time) in the model (in case of negative feedback). The visual and auditory times were assumed to be at the ACT-R default values of 185 ms and 100 ms, respectively.

Sub-Symbolic level of the Simon/SRC model

In ACT-R, each instance (or chunk) has an activation value that is used for retrieval in the recognition phase of the IBLT modeling process. An instance is retrieved from memory if the activation exceeds a retrieval threshold (RT), which sets the minimum activation with which an instance can be retrieved, and if the activation is the highest of all other instance activations at the time of retrieval. ACT-R defines activation of an instance as:

$$A_i = B_i + \sum_l PM_{li} + \varepsilon \quad (1)$$

where B_i is the base-level activation and reflects the recency and frequency of practice of the i th instance, which is given by

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-d}\right) \quad (2)$$

where n is the number of presentations of the i th instance in the past; t_j is the time since the j th presentation; and d is the decay parameter (bll) which is usually set at 0.5.

Specification elements l in the PM summation are computed over the slot values of the retrieval instance specification (i.e., the current task context). Match Scale P reflects the amount of weighting given to the similarity in the slot l , which is a constant across all slots with the value set at 1.0. Match Similarities M_{li} represents the similarity between the value l in the retrieval specification and the value in the corresponding slot of the instance i . The PM mechanism as described above determines similarity between the retrieval specification and the potential retrievable instances in DM. We used a function to calculate the degree of similarity based on the absolute value of distance between Color, Position and Orient slots of the retrieval specification and the instances stored in DM.

Finally, ε is the noise value, which is composed of two components; a permanent noise associated with each instance and an instantaneous noise computed at the time of a retrieval request. Both noise values are generated according to a logistic distribution characterized by a parameter s . The mean of the logistic distribution is 0 and the variance σ^2 is related to the s value by

$$\sigma^2 = (\pi^2/3) s^2 \quad (3)$$

We set the instantaneous noise s value in the IBLT model to make it a part of the activation equation.

For the purpose of modeling the Simon/SRC task, the parameters described above had the values given in Table 2.

Table 2: IBLT (ACT-R) Parameters with Values

Parameter/Slots	Value
RT	-1.0
bll	0.5
s	0.25
P	1.0
Color Slot Value	G = 3, R = 5, W = 0
Orient Slot Value	H = 3, V = 5, NO = 0
Position Slot Value	Lt = 0, Rt = 1

Running the IBLT Model in the Simon/SRC Experiment

The Simon/SRC task used for the experiment was originally developed in VB, and to make things compatible we used a VB version of IBLT that we have developed and calibrated to ACT-R (in LISP), reported in another research report (Dutt, Gonzalez & Lebiere, in preparation).

We ran a total of 32 dummy model participants (the same as the number of human participants in the experiment) using exactly the same task software used to conduct the human experiment. Human participants were provided with a few practice blocks prior to the test blocks (see descriptions of the method). The collected human data revealed a high accuracy in the first block of the experiment, which suggests that the participants had obtained a certain amount of familiarity with the task prior to beginning the experiment. Therefore, the model performed two blocks of the practice phase (32 trials x 2) prior to the test trials to make the initial level of model performance comparable to that of human subjects.

Soon after the model completed the practice blocks, it was run in the experiment. The model's data on the Simon/SRC task was recorded by the task software in a text file. We later analyzed and compared the data collected from the model runs to that collected earlier on humans using commonly employed metrics R^2 (for trend) and Root Mean Squared Error (RMSE; for closeness of fits). We used response time as our dependent variable for the purpose of analysis in this paper.

Model Fits

In the present paper, we focus on two main aspects of the human data; practice and sequential effects. To examine practice effects, we first analyzed the human data across the four learning blocks separately for Simon Corresponding trials, Simon Non-Corresponding trials, SRC Compatible trials, and SRC Incompatible trials. Figure 1 presents the practice effects observed from human participants and those generated by the IBLT model (error bars show 90% confidence interval around the point estimate). For human data, RT decreases with Block for all four conditions, and the shape of the functions shows typical learning curves.

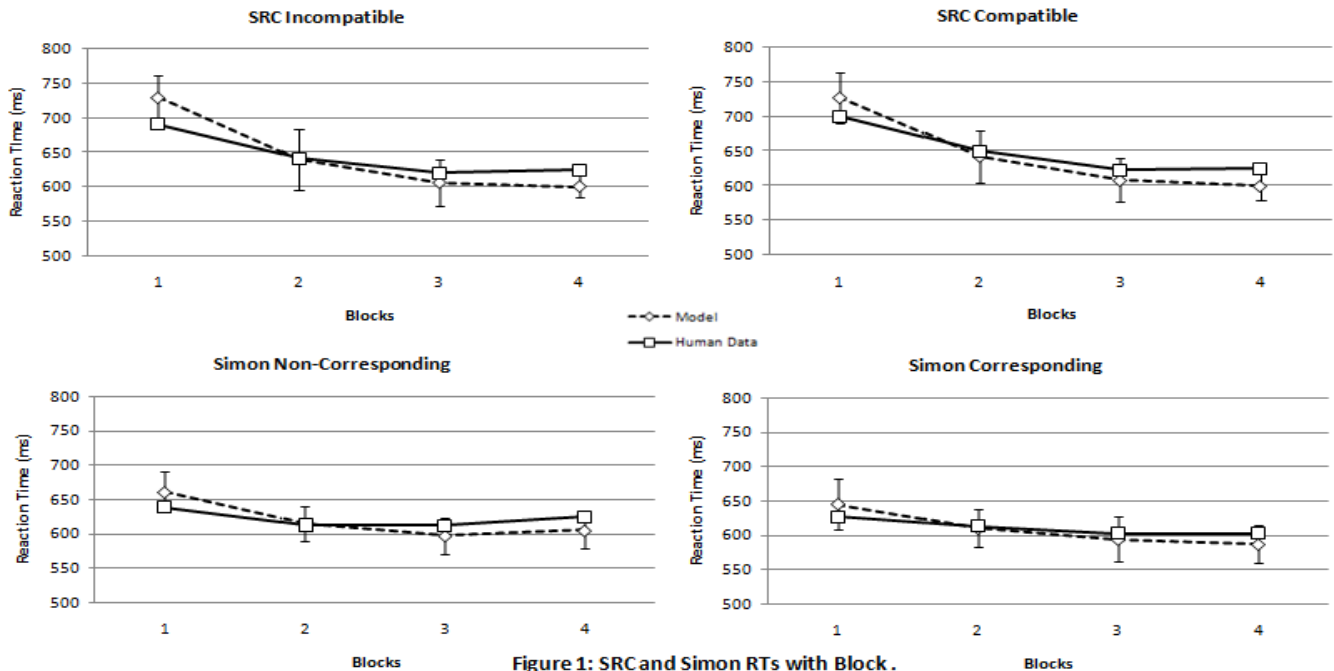


Figure 1: SRC and Simon RTs with Block. The R^2 and RMSD are reported in text.

The model output mimicked the human results, indicating that the IBLT model learned to perform the task in a similar way as human subjects did. The fit of IBLT model to the human data had $R^2 = 0.93$ and $RMSD = 80.54$ ms (Simon Corresponding trials), $R^2 = 0.64$ and $RMSD = 84.54$ ms (Simon Non-Corresponding trial), $R^2 = 0.98$ and $RMSD = 61.21$ ms (SRC Compatible trials), and $R^2 = 0.97$ and $RMSD = 62.96$ ms (SRC Incompatible trials), respectively.

To examine sequential effects, we analyzed response times as a function of Task Sequence (repeat/switch) and Mapping Sequence (repeated/switched) separately for the four trial conditions. Figure 2 (on next page) summarizes the results (error bars show 90% confidence interval around the point estimate). The trend is clear: When both task and mapping repeated, response times were reduced in both model and human data. Similarly, when both task and mapping switched, response times increased both in model and human data. The model outputs show similar patterns. The fit results are $R^2 = 0.96$ and $RMSD = 24.87$ ms, for the Simon Corresponding trials, and $R^2 = 0.91$ and $RMSD = 31.32$ ms for the Simon Non-corresponding trials. For the SRC trials, the model fits had $R^2 = 0.97$ and $RMSD = 15.86$ ms for the Compatible trials, and $R^2 = 0.95$ and $RMSD = 28.82$ for the Incompatible trials.

Discussion

As shown, model fits were generally good with respect to practice and sequential effects in the present experiment, suggesting that the IBLT model provides a good account for performance in the mixed SRC/Simon task. The learning effect in the model is explained by the IBLT process and the ACT-R mechanisms involved, in which similarity and activation play a key role.

Because the IBLT model uses only the correct instances in the selection of a response, the activation of the correct instances becomes much higher due to their repeated use and this increase in activation reduces the retrieval time for these instances. Thus, more and more correct instances are accumulated and retrieved, so that the model gradually transfers from an exploration phase (random judgment and retrieval of incorrect instances) to an instance exploitation phase (consistent retrieval of correct instances), thereby reducing reaction time over trials. The human RT for Simon Non-Corresponding trials in Figure 1 shows a slightly U-shape pattern where the RT increases for the last two blocks. On the other hand, due to recency and frequency effects just described the IBLT model reduces RT even for those two blocks. This is the reason why the fits for this condition, particularly for R^2 , are poorer compared to other fits.

Similarly, the sequential effects in the IBLT model occur because when the task and mapping repeat, the instance used on the previous trial has higher activation due to recency of its use. This increases the probability of that instance being retrieved on the current trial. Similarly, this instance-based retrieval also provides the explanation for the outcome that response times were longer when task and mapping switched.

The present model can also be used to generate predictions in novel situations (Dutt & Gonzalez, 2008). Several generalizations of the model are possible. One candidate for such a generalization is changing the proportion of the SRC and Simon trials in the experiment. The current IBLT model was implemented for an experiment where the numbers of the Simon and SRC trials are equal and thus their occurrences are equally likely on each trial. One could create situations in which the numbers of these trials are unequal, so that their likelihoods of

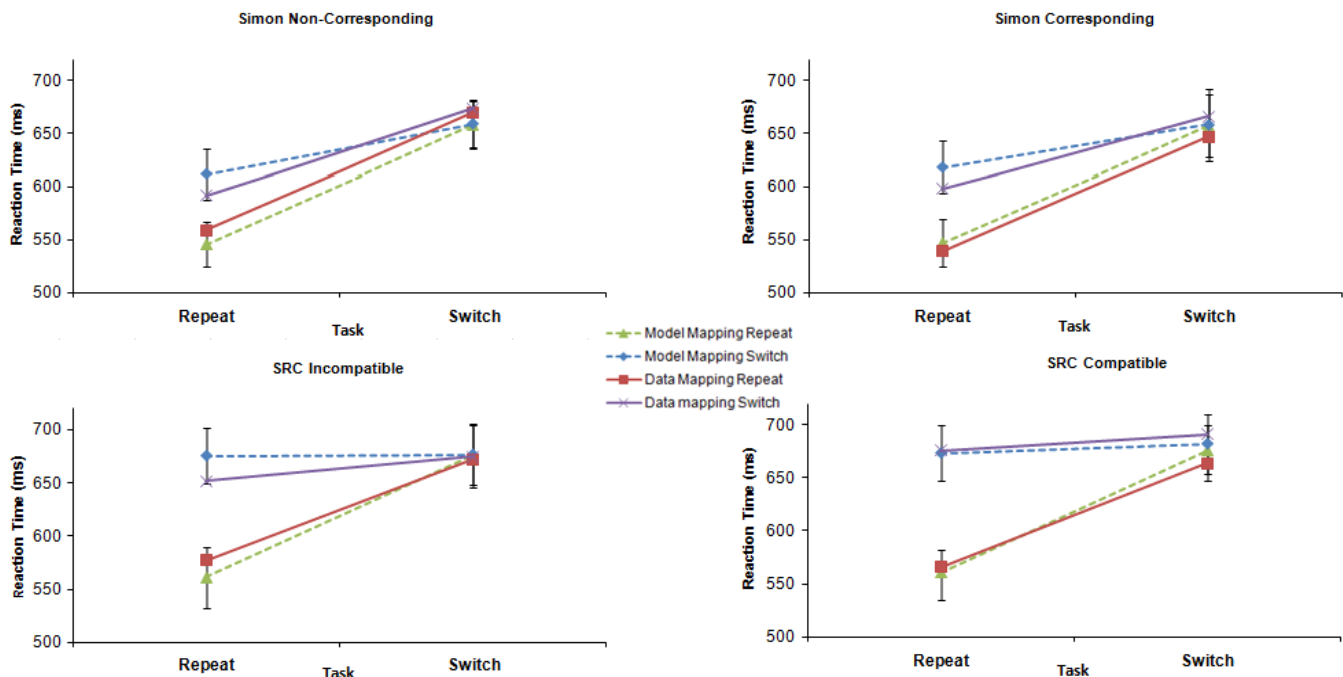


Figure 2: Task Repeat/Switch and Mapping Repeat/Switch. The R^2 and RMSD are reported in text.

occurrences are biased. Another possibility is the condition where payoffs of correct/error responses for the Simon and SRC trials are varied. For example, rather than using a tone to indicate incorrect trials, we could use monetary payoffs as feedback to the model and create conditions in which correct decisions on certain trial types are reinforced, and incorrect decisions are penalized, more than those on other trial types. Also, although the present experiment mixed location-relevant and location-irrelevant tasks, the current model can be used to predict human behavior in pure SRC or Simon tasks. This is because the model's current SDU structure does not change across the Simon and SRC trials.

The IBLT model discussed in the present paper has a general structure that, when coupled with the general functioning of the IBLT approach, provides a starting point for future investigations in the present research field. The current IBLT model can be used in a wide range of experimental conditions to generate predictions for novel tasks without major changes in the model structure, before a human experiment is conducted.

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