

Control by action representation and input selection (CARIS): a theoretical framework for task switching

Nachshon Meiran · Yoav Kessler · Esther Adi-Japha

Received: 24 June 2007 / Accepted: 6 February 2008
© Springer-Verlag 2008

Abstract Control by action representation and input selection (CARIS) is a modeling framework for task-switching experiments, which considers action-related effects as critical constraints. It assumes that control operates by choosing control parameter values, representing input selection and action representation. Competing CARIS models differ in whether (a) control parameters are determined by current instructions or represent a perseveration, (b) current instructions apply to the input selection and/or to action representation. According to the chosen model (a) task execution results in a default bias in favor of the executed task thus creating perseverative tendencies; (b) control counteracts these tendencies by applying a transient momentary bias whose locus (input selection or action representation) changes as a function of task preparation time; (c) this happens because the task-cue (e.g., SHAPE) initially attracts attention to the immediately available cue-information (e.g., target shape) and then attracts it to inferred or retrieved information (e.g., “circle” is related to the right key press).

Introduction

Long-term adjustment to novel situations is often achieved through learning. However, in the short term, when the

behavioral goal is changed, one may be required to act in a manner discordant with the learned skill or habit (Desimone & Duncan, 1995; Miller & Cohen, 2001; Norman & Shallice, 1986). The fact that humans are equipped with the ability to flexibly respond to such changing environmental constraints without being enslaved to their learning history is one key feature in their successful adaptation. Failures in such flexible thought and action have long been associated with psychopathology (e.g., Fey, 1951), underdeveloped cognition (e.g., Zelazo & Frye, 1997), and maladaptive behaviors following brain damage (e.g., Milner, 1964). These are among the reasons why the study of the mechanisms underlying the flexibility of human cognitive control has attracted so many researchers over the past two decades.

The present study attempts to generate an elaborate quantitative model for a widely studied experimental paradigm that examines human flexibility: task switching. While the elaborate account refers to task switching, it potentially relates to how attention is used for action control in changing task contexts in general. We call this modeling framework Control by Action Representation and Input Selection, or CARIS, for short. While CARIS builds on earlier works from our lab (Meiran, 2000a, but see also Meiran, 2000b; Meiran & Marciano, 2002) it provides a drastically different account of the phenomena under study as explained in the [General discussion](#).

In the first section of the article, we present the theoretical framework. In the second section, we present our mathematical theory, which we then develop into several alternative models. This mathematical theory is, to the best of our knowledge, the first theory that provides a unified explanation for switching, preparation, and action-related effects on mean reaction time (RT), RT distributions and error rates. In the third part, we use CARIS to model results

N. Meiran (✉) · Y. Kessler
Department of Psychology, Zlotowski Center for Neuroscience,
Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel
e-mail: nmeiran@bgu.ac.il

E. Adi-Japha
Department of Education, The Gonda Center for Brain Research,
Bar-Ilan University, Ramat-Gan, Israel

from an experiment comparing switching between object-based tasks (SHAPE and SIZE) and between spatial location tasks (UP-DOWN and RIGHT-LEFT; Yehene & Meiran, 2007). The results of a study which validated the modeling conclusion follow. The implications for other theories as well as the potential extensions and limitations of CARIS are discussed in the [General discussion](#).

Broad theoretical issues

In the present work, we used CARIS to model results from the cuing version of the task-switching paradigm (see Meiran, 2008a; Monsell, 2003, for recent reviews). The specific cuing paradigms that we used here are depicted in Fig. 1.

To explain CARIS conception, we adopt a distinction originally proposed by Narzis Ach in 1910 (Ach, 1910/2006). He wrote “The success and thus the efficiency of the will depend, on the one hand, on the determination, on the other hand, on the obstacles opposing the determination.” (Ach, 1910/2006, p. 5). Note that inner obstacles are relative. For example, Ach studied habit as an inner obstacle despite the obvious fact that habit and habit formation

are usually beneficial and become obstacles only in the relatively rare situations in which one needs to act against them. In task switching, perseverative tendencies create inner obstacles. Using Ach’s terms, will power is needed to ensure that the currently instructed task gets executed even when there is a strong tendency not to execute it. According to this framework, the observed behavior reflects a struggle between opposing forces, making the estimation of the separate contributions of these forces a formidable challenge. Accordingly, some theories emphasize the role of the “will” in proposing a time-consuming process of task implementation (e.g., Meiran, 1996; Rogers & Monsell, 1995; Rubinstein, Meyer, & Evans, 2001). Other theories emphasize the “inner obstacle”, by emphasizing the inertia of task sets (Allport, Styles, & Hsieh, 1994) or the unintended retrieval of the previously relevant task rule (Allport & Wylie, 2000; Waszak, Hommel, & Allport, 2003). Intermediate positions were offered by Koch and Allport (2006), Meiran, Chorev and Sapir (2000), Meiran and Daichman (2005), and Yeung and Monsell (2003a) among others.

The chosen CARIS model suggested that both the “will” and the “inner obstacle” operate simultaneously and that at a given moment, each of them influences a

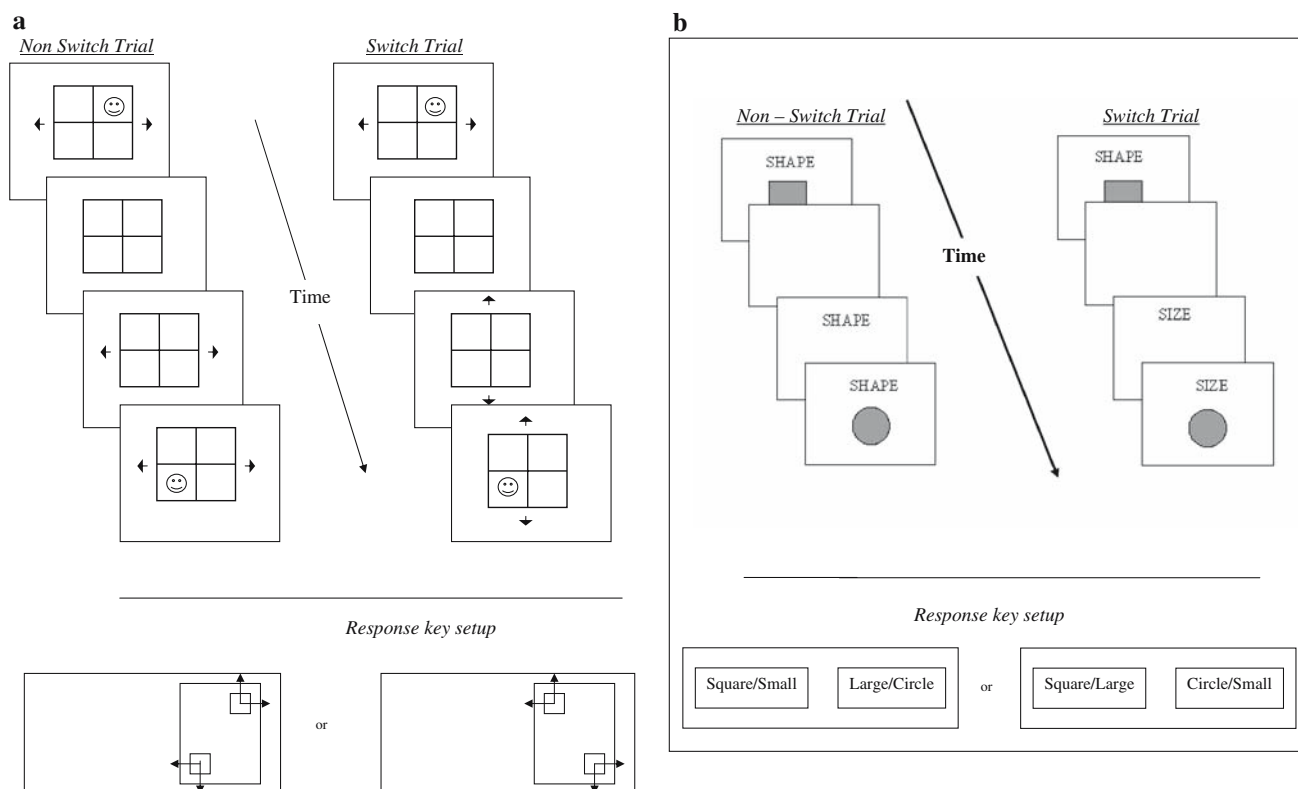


Fig. 1 Schematic representation of the two task switching paradigms. Each response key was associated with two categories. For the Spatial Paradigm, the Categories (UP, DOWN, RIGHT and LEFT) are indicated by *arrows*

separate component of the response selection apparatus. An especially dramatic example for a case in which the “will” operates on one behavioral component and the inner obstacle operates on another component was described by Diamond (1985) who studied Piaget’s (1954) A-not-B task. In this task, infants were required to reach to the location where an object was previously hidden. Diamond reported that infants occasionally look towards the correct location at the very same moment that they are reaching perseveratively to the incorrect location, which was correct beforehand. In these cases, the looking apparatus is presumably controlled by the “will”, whereas the reaching apparatus is controlled by the inner obstacle. Note that one implication is that the term “task” does not reflect a unitary representation (or a unitary “task set”). Instead, we view tasks as ad hoc configurations of control parameters (see also Logan & Gordon, 2001).

The second broad issue concerns the distinction between reactive and proactive control (e.g., De Pisapia & Braver, 2006). Specifically, De Jong (2000), Monsell and his colleagues (e.g., Monsell & Mizon, 2006; Rogers & Monsell, 1995), Rubinstein, et al. (2001), Sohn and Anderson (2001), our group (Meiran, 1996, 2000a; Meiran, Chorev, & Sapir, 2000) and others have emphasized proactive control; the notion that the relevant task rule must be implemented before the task is being executed. When the target stimulus is presented too early, the implementation of the relevant rule continues (because the task cannot yet be executed) and this adds to RT. According to these theories, this added RT is reflected in task-switching effects. In contrast, others, especially Allport et al. (1994), Allport and Wylie (2000), Waszak et al. (2003), and Yeung and Monsell (2003a) emphasized a more reactive form of control in which the information concerning the currently relevant task serves to bias processing online (and not in advance). According to the reactive view, the increase in RT in switch trials does not reflect task implementation time but reflects the increased time taken for the system to settle on a unique solution. We interpret the CARIS model that we eventually endorsed in the present work as supporting the reactive control position. Note that here we adopt a different view than in our previous works (especially Meiran, 1996, 2000a, 2000b; Meiran, Chorev, & Sapir, 2000).

Relevant background on task switching

Research using the task-switching paradigm has generated a number of replicable phenomena, which CARIS explains. Because our model provides an account of these phenomena, we will simply describe them at this point. Their

theoretical account will be provided in the [General discussion](#).

Switch cost and mixing cost

Following Fagot (1994), we discriminate between three types of trials. Single-task trials are taken from experimental blocks without task switching. Switch trials are those in which the task has changed relative to Trial $n - 1$. Repeat trials are taken from task switching blocks but involve a repetition of the task from Trial $n - 1$. We term the difference in performance between switch trials and single-task trials, *task-alternation cost*. The task alternation cost is separated into two effects which are additive by definition: the *task switch cost* (switch trials minus repeat trials) and the *task mixing cost* (repeat trials minus single task trials). As the terms suggest, switch cost is an effect associated with having just switched to a new task. In contrast, mixing cost may reflect more of an ongoing state (see especially Braver, Reynolds, & Donaldson, 2003; Los, 1996). However, it may also reflect transient control processes that are common to switch and repeat trials but are absent, or present to a lesser degree, in the single-task baseline (e.g., Altmann, 2007; Rubin & Meiran, 2005, see also Woodward, Meier, Tipper, & Graf, 2003).

Action-related effects in task switching

There is a growing body of evidence for the pervasive involvement of action-related effects in task switching. Accordingly, a relatively unique aspect of CARIS is the focus on action-related experimental manipulations, which we define as those related to the physical response (see also Gilbert & Shallice, 2002; Meiran, 2000a; Kleinsorge & Heuer, 1999). Our model explicitly accounts for two such effects but can explain the other effects too (see [General discussion](#)).

The task-rule congruency effect

Figure 2 describes the mapping of stimuli to responses in an experiment involving SHAPE and SIZE judgments. For some participants, the right key indicated both LARGE and CIRCLE, depending on which task was executed, and the left key indicated both SMALL and SQUARE. The solid arrows in Fig. 2 indicate the mapping for the SHAPE task, and the dashed arrows indicate the mapping for the SIZE task. Note that the mapping is identical for two of the objects, namely large-circle and small-square. When these objects serve as target stimuli, the trials are considered *congruent*. In the case of the other two objects, the trials are considered *incongruent*, because in these cases the correct response depends on

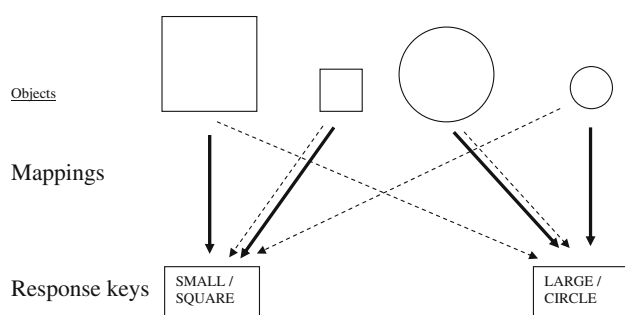


Fig. 2 Task rule congruency demonstrated for the object paradigm. For congruent trials, the stimulus-response mapping was the same for the two tasks, whereas for incongruent trials the mapping depended on the task

the task. Typically, congruent trials produce faster and more accurate responses than incongruent trials, and the difference between the respective RTs is the congruency effect. The effect was first reported by Sudevan and Taylor (1987) and a recent review of the relevant literature is provided by Meiran and Kessler (2008).

Reversal of the response repetition effect in switch trials

When participants perform a choice RT task, they respond more quickly when they repeat their response from the preceding trial (Campbell & Proctor, 1993; Pashler & Baylis, 1991). Interestingly, the response repetition effect is reversed in switch trials (see Fagot, 1994; Kleinsorge & Heuer, 1999; Meiran, 1996; Rogers & Monsell, 1995, for early examples; see Hübner & Druey, 2006; Mayr & Bryck, 2005; Schuch & Koch, 2004, for recent works). Repetition effects are not always found when the response categories are arbitrary (Campbell & Proctor, for choice RT; Ruthruff, Remington, & Johnston, 2001, for task switching, but see Kleinsorge, 1999). This result suggests that the repetition effects are (usually) mediated by meaningful response codes such as LARGE, CIRCLE, and so forth (see further Schuch & Koch, 2004).

Costs related to changing response meaning

Task switching often involves a change in response meaning (e.g., see the paradigm described in Fig. 1), and this change, in itself, contributes to switch costs. Meiran and Marciano (2002) found that a mere change in response meaning, without a change in the relevant stimulus dimension, caused a marked switch cost. Brass et al., (2003), Mayr (2001), and Meiran (2000b, 2005) compared two response setups. In the bivalent response setup, the responses of the two 2-choice RT tasks were mapped to the same set of two keys. Take the SHAPE-SIZE paradigm

(Fig. 1) for example. In this paradigm, one key is used for both SQUARE and LARGE. Consequently, a switch from the SHAPE task to the SIZE task, for example, involves a change in key meaning (from SQUARE to LARGE). In the univalent response setup, each meaning was assigned to a separate key-press. Because a key press indicated the same meaning throughout the entire experiment, a task shift did not entail a key-meaning change. The results indicated considerably larger switch costs with bivalent response setups (where task switching entails a key-meaning change) than with univalent response setups.

Reduction or elimination of switch costs in trials following no-go responses

Schuch and Koch (2003, see also Hoffmann, Kiesel, & Sebald, 2003; Koch & Philipp, 2005; Philipp, Jolicœur, Falkenstein, & Koch, 2007; Verbruggen, Liefoghe, Szmalec, & Vandierendonck, 2005; and Verbruggen, Liefoghe, & Vandierendonck, 2006) found that switch costs are eliminated following trials in which participants were instructed to withhold from responding.

Finally, Steinhauser and Hübner (2006) found switch *benefits* when the previous trial involved an error. Errors in incongruent trials usually reflect the execution of the wrong task (Meiran & Daichman, 2005). Accordingly, the results of Steinhauser and Hübner show that switch cost results, in part, from the binding of task-related categories with physical response codes. Namely, when there was an error in Trial $n - 1$, what is nominally a task-switch is actually a task repetition and what is nominally a task repetition is actually a task switch.

CARIS

CARIS is a modeling platform that enables the formulation of a variety of competing models, all of which share the core assumptions.

Core assumptions

Levels of representation

CARIS deals with two distinct levels of representation. The first level is pre-selective and it contains information relevant to all the switched-between tasks without prioritizing any of the tasks. The second level of representation is that which enters response selection. The information in that level is a transformed version of the pre-selective information, where greater weight is given to information that is relevant to one task as compared to other tasks. In CARIS, the pre-selective representation of the target stimuli is one

that had already gone through earlier forms of selection such as those studied in the context of orientation (e.g., see Lavie, 1995; Pashler, 1991; Shalev & Algom 2000, for evidence regarding multiple levels of selection). For example, the pre-selective target information in the SHAPE-SIZE paradigm described in Fig. 1 involves the shape and the size with equal emphasis. The post-selective information is one in which an emphasis is given to one dimension (shape or size) at the expense of the other (size or shape).

Shared representational medium for perceived stimuli and actions

A relatively unique aspect of CARIS is the explicit assumption of a direct interaction between perception-related (stimulus) and action-related (response) codes. Hommel, Müssler, Aschersleben, and Prinz (2001) have reviewed a large body of research that supports this assumption. This interaction is so direct that CARIS assumes that at least some action codes are identical with some stimulus (input) codes so that the “similarity” between input and action can be determined. In other words, CARIS deals with very abstract codes.

The formation of the abstract input and action codes can be described in terms of two transformations. We explain them in reference to an example. Suppose that the target stimulus is a LARGE SQUARE, the right key indicates LARGE and CIRCLE, the left key indicates SMALL and SQUARE, and the task is SIZE. (For reasons of clarity, we present the two translation operations in all-or-none terms. A more precise description will follow.) The first transformation can be represented schematically as

[Target = LARGE SQUARE]
→ [Target Representation = LARGE].

This operation involves *input selection*. The other transformation may be represented schematically as

[Key = LARGE CIRCLE]
→ [Key Representation = LARGE]

where “Key” stands for a motor act such as pressing the right key. Based on earlier works reviewed by Hommel et al. (2001), we assume that manual motor acts (especially those involved in choosing between two response keys) are likely to be represented spatially. This operation involves *action representation*. Input selection and action representation stand for selective-attention sets, called the *Input-Set* (or I-Set) and *Action-Set* (or A-Set), respectively. In Meiran’s (2000a) model, which is CARIS predecessor, they were termed Stimulus-Set (S-Set) and Response-Set (R-Set), respectively. We prefer the new labels because they have broader and more generic implications. For

example, the term “action” is not restricted to responses and may relate to spontaneously chosen movements. This implies that CARIS predicts that changes in A-Set will also influence spontaneously chosen actions.

Graded selection is possible

In CARIS, the operation of the I-Set and A-Set is expressed in terms of the proportion of task-relevant information, which is selected to enter the post-selection phase. CARIS allows input selection and action representation to be graded in nature, like in Treisman’s (1969, cf., Ward, 1982) classic model. For example, graded selection of the relevant information (say, size) for a LARGE SQUARE target may be represented schematically as vividly representing the LARGE information with a faint representation of the information SQUARE (i.e., Representation = LARGE-SQUARE). Note that CARIS allows selection to vary along a continuum ranging from no selection to full (all-or-none) selection. As such, it represents all-or-none selection as a special case.

Response selection by similarity

A related assumption is that response selection is based on a computation of the similarity between the (filtered) representation of the target stimulus and the (filtered) representations of the alternative responses, so that the response that is “most similar” to the target stimulus is chosen. Similarity is computed in CARIS in a manner strictly analogous to that of Hintzman’s (1986) MINERVA model.

A schematic description of CARIS architecture

Figure 3 presents a schematic description of the CARIS architecture. CARIS is described by a series of equations that link CARIS core parameters to the predicted RT. The core parameters refer to input selection (w_I), action representation (w_A), and the binding of response-codes with response meanings, w_{CR} , (CR standing for category-response binding). This last parameter affects the response representation of the repeated response (see subsequently). These core parameters are given in units of bias, ranging from 0 (all the weight given to Task A-related information) to 1 (all the weight given to Task B-related information) through 0.5, which indicates that no selection has been performed and that the two pieces of information (e.g., the figure’s shape and size) receive equal weights.

Because CARIS explains switch cost and mixing cost, as described later, it includes two additional parameters, representing the *unexplained* switch cost and mixing cost,

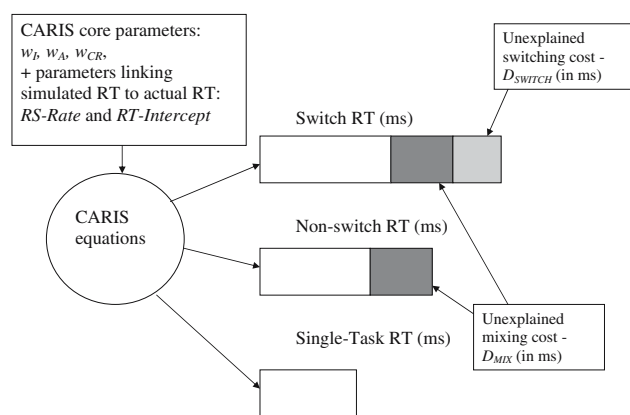


Fig. 3 A schematic representation of CARIS

D_{SWITCH} and D_{MIX} , given in ms units. In some respects, these parameters are similar to disturbance terms in Structural Equations Models (Loehlin, 1987), which represent the reliable but unexplained variance. Unlike the usual treatment of disturbance terms, D_{SWITCH} and D_{MIX} are given a processing interpretation. CARIS assumes that the processing of the task cue results in choosing an abstract task representation (the task vector, see later). Accordingly, D_{MIX} is interpreted as task decision time. Given the task uncertainty in the cuing paradigm, this task decision process is assumed to take place in switch and repeat trials (cf. Altmann 2007; Gade & Koch, 2007a; Koch, 2005; Meiran, 2008b; Rubin & Meiran, 2005). D_{SWITCH} is interpreted as the reduction in cue processing time due to cue repetition (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). Importantly, the addition of these duration parameters was not responsible for the high model fit we observed. Omitting these parameters from the chosen model resulted in a tiny (but significant) drop in model fit that retained an acceptable level by current standards.

The CARIS core

Representation of stimuli and responses

In CARIS, stimuli and responses are presented in the same manner, as ordered vectors. In the two-tasks, two-responses per task scenario being modeled here, the vectors have four elements, with the first two entries representing the values in one dimension (e.g., CIRCLE and SQUARE, in the shape dimensions) and the next two positions representing the values in the second dimension (e.g., SMALL and LARGE, the values of the size dimension). Each of the entries is assigned one of two values “1” for “present” and “0” for absent. Accordingly, letting the ordering be (*large small circle square*) a *large circle* stimulus is represented as:

$$S_{\text{LARGE-CIRCLE}} = (1 \ 0 \ 1 \ 0)$$

and a response indicating both LARGE and CIRCLE is represented identically, as:

$$R_{A(\text{LARGE-CIRCLE})} = (1 \ 0 \ 1 \ 0)$$

In the example presented here, there are two response keys $R_A = (1 \ 0 \ 1 \ 0)$ and $R_B = (0 \ 1 \ 0 \ 1)$ where R_B is used to indicate SMALL and SQUARE.

How control is achieved

Task control in CARIS is represented in two distinct processes: An all-or-none task decision process and a graded rule-implementation process. Task decision is based on cue processing and its product is an abstract task representation. This representation is then translated into a more concrete representation, which enables the filtering of irrelevant information. Finally, the filtered information serves for response selection. (We cannot rule out the possibility that such a straightforward translation from a cue to an abstract task representation may be restricted to conditions in which the task cues are clearly visible, remain on the screen and indicate the task with perfect validity.)

Task decision

Cue encoding results in determining the abstract required task identity (e.g., Arrington, Logan & Schneider, 2007). In CARIS, this task decision process results in endorsing one task and not the other task. It is therefore an all-or-none decision between two mutually exclusive alternatives. Task identities are represented by *task vectors*. The vector representing the SIZE task is $T_{\text{SIZE}} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and the vector representing the SHAPE task is $T_{\text{SHAPE}} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$.

Rule implementation

Once the task has been chosen, there is a process that translates this abstract task identity into a more concrete *biasing vector* (e.g., W_{SIZE} and W_{SHAPE} are the biasing vectors in the SHAPE-SIZE paradigm). This is represented by a process of matrix multiplication in which a *general purpose biasing matrix* is multiplied by the task vector, resulting in a biasing vector which suits the task at hand. The general-purpose biasing matrix W is filled with w -values ($0 \leq w \leq 1$) representing the *graded* bias in favor of the preferred dimension. This general purpose matrix is:

$$W = \begin{pmatrix} w & 1-w \\ w & 1-w \\ 1-w & w \\ 1-w & w \end{pmatrix}$$

Regarding the specifics, although we present w as a single parameter for brevity, it stands for two separate parameters, w_I , representing input selection and w_A , representing action representation. Accordingly, there are two general purpose matrices, W_I and W_A , containing the parameters w_I and w_A , respectively.

When multiplied by the SIZE vector, the resultant vector is:

$$W \cdot T_{\text{SIZE}} = W_{\text{SIZE}} = \begin{pmatrix} w \\ w \\ 1-w \\ 1-w \end{pmatrix}$$

and when multiplied by the SHAPE vector it is:

$$W \cdot T_{\text{SHAPE}} = W_{\text{SHAPE}} = \begin{pmatrix} 1-w \\ 1-w \\ w \\ w \end{pmatrix}$$

One may think of the selection vectors, W_{SIZE} and W_{SHAPE} as filters determining which information will enter into response selection. These filters may be set by the current goal (will), as determined by the processing of the task cue, or by the immediate past experience (inner obstacle).

The information eventually passing through the filter is computed by multiplying the input information, S , and/or the response representation information, R_A and R_B , by the selection vector, W_{SIZE} or W_{SHAPE} . Accordingly, there is a reference in CARIS to filtered representations, S_{FILTERED} , $R_{A\text{-FILTERED}}$, and, $R_{B\text{-FILTERED}}$, for the input and two responses, respectively. Because the computation is the same for the target stimulus and the two responses, we present just one example, describing how selection applies to the target stimulus. The example describes the formation of the filtered representation of a large-circle stimulus (or the representation of a response denoting LARGE and CIRCLE) in a context in which the SIZE task dictates the selection. The first step is generating the filtered representation of the stimulus by multiplying corresponding elements of the stimulus vector and the selection vector, an operation denoted by the symbol “*.”. Namely,

$$\begin{aligned} S_{\text{LARGE-CIRCLE/FILTERED-SIZE}} &= S_{\text{LARGE-CIRCLE}} \cdot W_{I\text{-SIZE}}' \\ &= (1 \ 0 \ 1 \ 0) \cdot (w_I \ w_I \ 1-w_I \ 1-w_I) \\ &= (w_I \ 0 \ 1-w_I \ 0) \end{aligned}$$

More generally: $S_{\text{FILTERED}} = S \cdot W_I'$ and $R_{\text{FILTERED}} = R \cdot W_A'$

To give a concrete numerical example, assume that instruction-based control operates via the filtering of irrelevant stimulus information, and that filtering efficiency is 0.90 (meaning that 90% of the relevant information passes the filter while only 10% of the irrelevant information passes it). In this case, the representation of a large-circle would be a strong representation of the attribute *large* with a weak representation of the attribute *circle*, that is (.9 0 .1 0). Note that the same example refers also to a case in which a given response key indicates both LARGE and CIRCLE, because the representation of that key (1 0 1 0) is the same representation used for the large-circle target just described.

Response selection in CARIS is based on two computational steps: (1) computing response potency as the similarity of the filtered stimulus representation with that of the filtered response representation, and (2) choosing the more potent response.

Response potency

Potency, which is a scalar (number) is separately computed for each response, as $P = S_{\text{FILTERED}} \cdot R_{\text{FILTERED}}'$. We will give an example. Assume that Response A is used to denote LARGE and CIRCLE, depending on the task, the target stimulus is a small-circle, the relevant task is SIZE and both the input and the action are controlled by the currently instructed task (SIZE). In this case, the response potency would be:

$$\begin{aligned} P_{\text{Response-A}} &= (0 \ w_I \ 1-w_I \ 0) \cdot \begin{pmatrix} w_A \\ 0 \\ 1-w_A \\ 0 \end{pmatrix} \\ &= (1-w_I) \cdot (1-w_A) \end{aligned}$$

Response selection

The response corresponding to larger potency value is the one which gets eventually selected. For example, if $P_{\text{Response-A}} > P_{\text{Response-B}}$ then Response A gets to be selected. Although there is likely to be a potency difference threshold, this is not currently implemented in CARIS.

Modeling RT

The RT is modeled in two conceptually separate computational steps. The first step involves computing response strength, or *Str*. The second step involves relating *Str* to the actual RT using a linear regression model. Response strength is defined as:

$$Str = 1/|P_{\text{Response-A}} - P_{\text{Response-B}}|$$

Using an inverse (1 divided by Str) transforms potency (in which potent = fast) to latency (in which a small number = fast). The denominator represents the response competition. If the competing responses are nearly equipotent, the denominator becomes small and Str becomes large.

The modeled RT, as predicted by the CARIS core is defined as:

$$RT' = RT\text{-Intercept} + Str \cdot RS\text{-Rate} + Mix \cdot D_{\text{MIX}} \\ + Sw \cdot D_{\text{SWITCH}} \quad (Mix = 0, 1, Sw = 0, 1)$$

where Mix refers to whether the trial is taken from the mixed tasks blocks ($Mix=1$) or from the single-task block(s) ($Mix=0$), and Sw refers to whether it is a switch trial ($Sw=1$) or not ($Sw=0$).

$RT\text{-Intercept}$ and $RS\text{-Rate}$ are estimated as a part of the model fitting process. The slope ($RS\text{-Rate}$, standing for “response selection rate”) estimates the rate of the processes being modeled in CARIS, which are, broadly defined, response selection (especially related to response potency and response competition) and related control processes. The $RT\text{-Intercept}$ is uninformative because it gives the RT in the case of $Str = 0$, a case which never exists. The smallest possible value of Str corresponds to a case in which there is perfect selection, a perfect similarity between one response and the target stimulus, and no competing response. This scenario exists when the (filtered) response vector and the stimulus vector are identical and indicate perfect selection as in the case in which both are (1 0 0 0). In such a case, $Str = 1$. Accordingly, RT in a case in which response selection takes a minimal time equals $RS\text{-Rate} + RT\text{-Intercept}$, a value we call “corrected intercept”. The corrected intercept represents the time taken by processes not modeled in CARIS such as the stimulus’ relatively shallow encoding and shallow response preparation.

CARIS formulation of the three generic models

The CARIS realizes various task control modes that are expressed by the generic models described shortly. These strategies differ from one another with respect to whether selection is instruction-based (and, by extension, intentional and controlled) or based on the immediate past experience (perseverative) and thus pose inner obstacles. When selection is instruction-based, the task vector, T , is based on the instructed task in Trial n (henceforth T_n). In contrast, when selection is perseverative, T comes from Trial $n - 1$ (henceforth T_{n-1}).

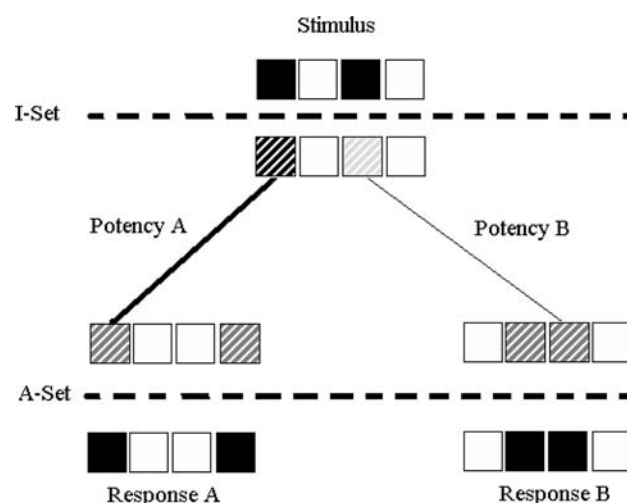


Fig. 4 A schematic representation of control according to Model 1. The Grayness Scale represents numbers ranging from zero (white) to unity (black). Each line of squares represents an ordered vector of attributes such as (large, small, circle, square). In the figure, the task in Trial n is SIZE, the target stimulus is a large circle. The correct (Left) response is selected because it shares an attribute that is emphasized in the target stimulus (large). However, the right response is also activated because it shares with the target a de-emphasized attribute (circle)

According to Model 1, correct response selection is ensured by filtering out irrelevant input information. In other words, this model assumes that input selection is controlled and action representation is perseverative. Figure 4 demonstrates how the correct response is selected in spite of the fact that action representation is not filtered at all. In describing Fig. 4, we will use a concrete interpretation, following the example we have used until now. This concrete interpretation refers to switching between SIZE and SHAPE judgments. Accordingly, the vectors represent the ordered attributes (large, small, circle, square). The target stimulus in the trial is a large-circle; the left response indicates either LARGE or SQUARE and the right response indicates either SMALL or CIRCLE (note that the trial being described is an incongruent one). The instructed task is SIZE. Accordingly, the filtered input has a strong (dark) representation of LARGE and a faint (light) representation of CIRCLE. Because the model assumes that control is based on input selection, the other aspect, action representation is not controlled and hence it is perseverative. Moreover, because action representation is perseverative (biased according to Task $n - 1$) and because (when there are random switches) these adjustments in the bias cancel each other out over trials (in the mixed tasks conditions), the filtered action representation gives a roughly equal weight to the two meanings associated with each response (gray, namely w_A roughly equals

0.50). The correct (left) response gains much potency (heavy line connecting the stimulus and the response) because LARGE is emphasized in the (filtered) input representation. The incorrect (right) response also gains some potency (thin line connecting the stimulus and the response), because some CIRCLE information passes the Input-Set filter and activates the corresponding response information. As a result, there is either response slowing (as in the figure, where the irrelevant information activates a competing response) or facilitation (when it activates the correct response). Figure 4 depicts a case in which the action representation is completely unbiased. Our estimates below suggest that (with little advance preparation) the action representation is slightly biased in favor of the task in Trial $n - 1$. In the case of a task repetition, this bias causes response facilitation. In the case of a task switch, it results in response slowing because the adjustment, based on Task $n - 1$, is done at the expense of Task n . Fitting CARIS Model 1 allows the estimation of the degree of input selection and the degree of bias in favor of Task $n - 1$ in action representations. For example, if the parameter w_1 is estimated to be 0.95, this implies that 95% of the relevant input enters response selection (for example, 95% of the size information if SIZE is the required task) but at the same time 5% (1-0.95) of the irrelevant input (shape information) also enters response selection. If w_A is estimated to be 0.53, for example, this means that action representation has been biased according to the $n-1$ task by 3% (0.53-0.50, where 0.50 represents unbiased representation).

According to Model 2 (Fig. 5), correct response selection is ensured by filtering out irrelevant information in the action representation (see Hommel, 1993). In other words, the model assumes that action representation is controlled and input selection is perseverative. Figure 5 demonstrates how a Model 2 strategy enables correct response selection. According to Model 2, input selection is biased in favor of Task $n - 1$ (e.g., Ward, 1982). The strong bias in action representation in favor of Task n is what ensures correct responding.

In Model 3 (Fig. 6), input selection and action representation are both instruction-based and controlled (dictated by Task n). Namely, irrelevant input information and irrelevant action representation information are both filtered out. Because both the input and the action representation are selected according to the present task, Model 3 does not involve a bias in favor of Task $n - 1$ aside from the bias made to the representation of the $n-1$ st response (see Response repetition).

Formally, the three generic models differ with respect to the computation of response potency, P . As mentioned before, all three generic models assume that $P = S_{\text{FILTERED}} \cdot R_{\text{FILTERED}}'$ and that the unexplained switch cost

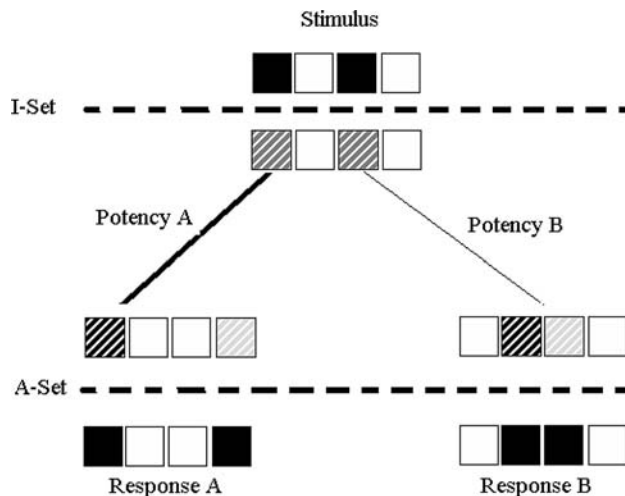


Fig. 5 A schematic representation of control according to Model 2. In the figure, the Task in Trial n is SIZE, the target stimulus is a large circle. The correct (Left) response is selected because the attribute “large” is emphasized in the response representation. However, the right response is also activated because it shares with the target a de-emphasized attribute (circle)

and mixed cost are represented by D_{SWITCH} and D_{MIX} , respectively. Their differences are as follows:

According to Model 1, $P = S_{\text{FILTERED}_n} \cdot R_{\text{FILTERED}_{n-1}}'$. The subscripts n and $n - 1$ refer to whether the representation is formed based on the instructed task in Trials n (representing the “will”) or $n - 1$ (representing the “inner obstacle”), respectively. According to Model 2,

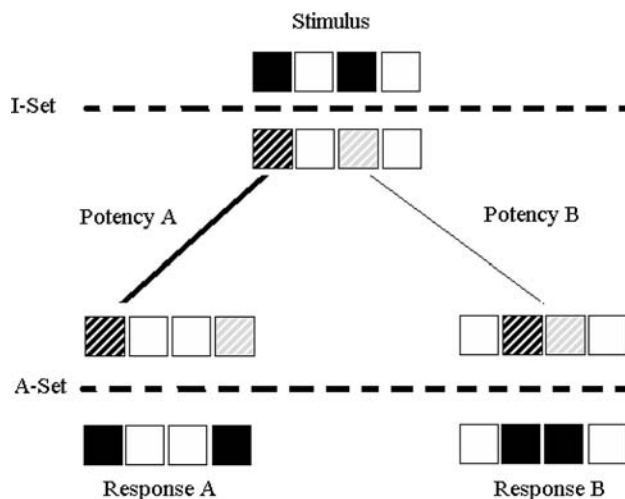


Fig. 6 A schematic representation of control according to Model 3. In the figure, the Task in Trial n is SIZE, the target stimulus is a large circle. The correct (Left) response is selected because the relevant attribute (large) is emphasized in both the target and the response, which makes their representations similar. However, the right response is also activated because it shares with the target a de-emphasized attribute (circle)

$P = S_{\text{FILTERED}_{n-1}} \cdot R_{\text{FILTERED}_{n-1}}$. According to Model 3, $P = S_{\text{FILTERED}_{n-1}} \cdot R_{\text{FILTERED}_{n-1}}$. Note that Model 4 in which $P = S_{\text{FILTERED}_{n-1}} \cdot R_{\text{FILTERED}_{n-1}}$ is also conceivable. However, such a model predicts that performance would be completely perseverative, as observed among some neurological patients (Yehene, Meiran, & Soroker, 2005, 2008). This model can be ruled out when accuracy in switch trials is high.

The bias made in favor of Task $n - 1$ in the various models can potentially accumulate over trials. Such an accumulated bias cannot be (consistently) found in mixed tasks conditions because bias in favor of one task is quickly canceled by an opposite bias in favor of the competing task. In single task condition, the bias is according to the same task in the entire block and this bias is likely to accumulate. For this reason, the parameter which represents a bias according to Task $n - 1$ has two separate instantiations: one for the mixed tasks condition and one for the single task condition. Accordingly, Model 1 has two separate action-representation parameters, w_A and $w_{A\text{-SINGLE}}$ for the mixed-tasks and single-task conditions, respectively. Model 2 has two separate input selection parameters, w_I and $w_{I\text{-SINGLE}}$, which represent input selection in mixed tasks and single-task conditions, respectively. Note that CARIS Model 3 does not assume that perseverative bias accumulates over trials because there is no task perseveration (aside from response repetition effects) in that model. As a result, the core parameters are the same in mixed tasks conditions and in single task condition. Also, because there is no bias in favor of Task $n - 1$ in Model 3, in this model, the entire difference between single-task conditions and mixed-task conditions is attributed to D_{MIX} . Also, note that Model 3 is still equipped, *in principle*, to explain congruency and response repetition effects. Congruency effects are possible if the controlled selection is imperfect, so that irrelevant input information can activate the wrong response in incongruent trials. Similarly, like all the other models, response representation is perseverative, leaving room for response repetition effects.

Hybrid models and proactive vs. reactive control

As the reader may recall, we distinguish between proactive and reactive control. Proactive control refers to the advance setting of the system that ensures task appropriate responding. When control is reactive, it is accomplished via online biasing that takes place simultaneously with the core processing. Our approach to decide between reactive and proactive control was to model results in two conditions, one with a short preparation interval, not giving much room for proactive control, and another one in which there was plenty of room for proactive control (long

preparation interval). Task preparation time was manipulated by the task-cue to target interval. According to our reasoning, proactive control is consistent with two broad scenarios. In one scenario, the same processing mode (represented by say, Model 1) characterizes both the short and the long preparation intervals (as in Meiran, 2000a). In the other scenario, Model 1 or Model 2 describes performance when preparation time is short. According to these models, only one aspect (input selection or action representation but not both) is controlled by the current (n th trial) task instructions. The results of the long interval are best described by Model 3 assuming that both aspects are controlled by the current (n th) task instructions. The reasoning was that, in this scenario, preparation time served to apply control in steps, beginning with one (input selection or action representation) and then adding the other (action representation or input selection) when preparation time permits.

There are hybrid models that are clearly inconsistent with the idea of proactive control. These include cases in which Model 1 is selected for the short interval and Model 2 is selected for the long interval (henceforth, Model 1–2) or vice versa (Model 2–1) and models in which Model 3 is selected for the short preparation interval and a less prepared model (Model 1 or 2) is selected for the long interval (Models 3–1 and 3–2).

We dwell on the interpretation of the latter models because one of them (Model 1–2) was chosen as the best description of the results in the present work. Consider Model 1–2, for example. According to this model, input selection is willed (based on the n th task) and action representation is perseverative (it is biased in favor of Task $n - 1$) when the preparation interval is short. The reverse holds for the long preparation interval. This implies that input selection that was willed became perseverative afterwards. This trend is clearly inconsistent with the proactive control idea according to which the system's parameters are changed according to the new task and retain their new value until the next task is required. Had this been the case, any parameter that was willed in the short preparation interval should have remained willed in the long interval (as in Model 1–3, for example).

Model 1–2 makes perfect sense if one makes the following assumptions: (1) task *execution* (or perhaps partial execution, see Hübner & Druey, 2006; Philipp et al., 2007) results in forming a default bias in favor of Task $n - 1$; (2) this holds true for all the parameters; (3) to ensure successful willed action, *transient* momentary top-down control signals bias the parameters and makes them willed. This is essentially reactive control; (4) that the I-Set was willed at one point while the A-Set became willed at a later point may be explained by assuming that top down control acts when a particular aspect (input or action) is in the

attentional focus. The idea here is that the task cue, besides providing the abstract task identity information may also direct attention immediately to either the input or to the action representation. At a later time point, when the cue is further processed, additional cue information is *derived or retrieved* and becomes focused. For example, the *dimension cue* SHAPE immediately attracts attention to the (input) dimension, shape. At a later time point, the action representation information is retrieved from memory and becomes focused. Consequently, such a cue is likely to result in applying the instructed task to the I-Set first (because the input dimension is initially focused) and applying it to the A-Set only later on, because action representation is not immediately available from the cue and needs to be derived or retrieved. In other words, dimension cues are likely to induce the strategy described by Model 1–2. In contrast, there are mapping cues, such as “CIRCLE SQUARE”, which indicate that the left key is used for “circle” responses and the right key is used for “square” responses. With these cues, action representation information becomes available quickly, whereas the input dimension (shape) information is inferred. Such cues are likely to shift performance towards Model 2–1 strategy. Below we provide experimental evidence for the final assumption.

An important note to make is that model choice cannot be based entirely on relative model fits. The chosen parameter values should accord with the chosen model’s assumptions. Take for example a hypothetical scenario in which Model 1 was selected by its fit for both intervals. To take this as evidence for proactive control, one of the following should occur. In comparison with short preparation, long preparation should reflect an improved input selection, lesser bias in favor of Task $n - 1$, or at the minimum, that the reverse trend should not be found. The reasoning here is that providing more time for selection should result in better (or at least not worse) selection. Moreover, either D_{SWITCH} or D_{MIX} should reduce, representing the time taken to improve selectivity ahead of the target stimulus. The reasoning here is based on the inserted preparation stage idea.

Response repetition

The fact that response repetition influences performance and that the direction of this influence depends on task switching imposes an important constraint on all the models. Specifically, these results suggest that for any model to be plausible, it must assume that perseveration takes place and at the level of the individual responses. Within CARIS, perseveration at the level of the individual response must take place in the A-Set (which discriminates between the two responses) and cannot take place in the

I-Set, which does not make such discrimination. Accordingly, all the models include an assumption that the selection vector for the repeated response is incremented by a small factor, w_{CR} (CR standing for category-response binding) in favor of Task $n - 1$. Specifically, $w_{\text{A-REPEAT}} = w_{\text{A}} + w_{\text{CR}}$ ¹. The presently modeled experiments and CARIS models cannot tell if this change in action representation is due to the strengthening of the particular category-response association, the inhibition of the unselected response category, the fact that the target stimulus retrieves task related response codes, or that a switch signal taking place at the level of the abstract task representation propagates uncontrollably to the level of the response (Kleinsorge & Heuer, 1999). Note that the inclusion of the w_{CR} parameter is informative in the sense that it provides a more parsimonious explanation than given by the standard ANOVA model. Specifically, the ANOVA provides a two *df* model of how task switching modulates response repetition effects. This is the interaction term between Switch (with 2 *df*) and Response Repetition (with 1 *df*). CARIS provides a more parsimonious account with only 1 *df*.

¹ A numerical example will clarify this point. In Model 1, response representation is perseverative. Let us assume for example that $w_{\text{A}} = 0.51$. A switch from SHAPE to SIZE would result in representing Response A and Response B as (.49 0 .51 0) and (0 .49 0 .51). (Note that in both the cases, the weight given to the relevant feature, size, is smaller than that given to the irrelevant feature, shape, reflecting the fact that shape was relevant in Trial $n - 1$). If the response used to indicate LARGE and CIRCLE is repeated $w_{\text{A-REPEAT}} = w_{\text{A}} + w_{\text{CR}}$ (where $w_{\text{A-REPEAT}}$ represents w_{A} for the repeated response) and the selection vector for Response A becomes

$$\begin{pmatrix} .49 - w_{\text{CR}} \\ .49 - w_{\text{CR}} \\ .51 + w_{\text{CR}} \\ .51 + w_{\text{CR}} \end{pmatrix} \text{ If } w_{\text{CR}} = .03, \text{ the selection vector for Response A in the}$$

present example becomes $\begin{pmatrix} .46 \\ .46 \\ .54 \\ .54 \end{pmatrix}$. Note that the selection vector is

translated into a response representation such as $\begin{pmatrix} .46 \\ 0 \\ .54 \\ 0 \end{pmatrix}$, for example.

This implies that the bias in favor of the emphasized dimension in Response A is increased relative to Response B, for which the bias

vector would be $\begin{pmatrix} .49 \\ .49 \\ .51 \\ .51 \end{pmatrix}$ with a response representation that may be

$\begin{pmatrix} 0 \\ .49 \\ 0 \\ .51 \end{pmatrix}$ keeping in line with the example. Given that the emphasis is

based on the $n-1$ st task, it is counterproductive in switch trials, and becomes even more counterproductive if the response is repeated.

Plausibility bounds on parameter values

All CARIS parameters have realistic bounds. First, all the core CARIS parameters assume values between 0 and 1, because they represent the proportion of information allowed to pass through the filter. Moreover, if the given CARIS model assumes that control is mediated by input selection (e.g., Model 1) whereas action representation is determined by Task $n - 1$, w_I should exceed w_A (or $w_A + w_{CR}$ for repeated responses), for otherwise the model would predict that in incongruent trials the wrong response would be more potent than the correct response and would therefore be selected (see explanation below). For the same reason, if the model assumes that control is based on action representation (e.g., Model 2), w_A should exceed w_I . Additional boundaries are imposed on D_{MIX} and D_{SWITCH} , which should be equal or larger than zero because it does not make sense to speak of a negative cue encoding time or task decision time. Finally, there are also boundaries on the regression parameters, *RS-Rate* and *RT-Intercept*. Specifically, *RS-Rate* must be positive, indicating that relatively fast responses are also relatively strong. Also, there is a practical boundary on the corrected intercept, $(RS-Rate + RT-Intercept) > \varepsilon$, where $\varepsilon > 0$, and more realistically is greater than about 250 ms (i.e., typical mean simple RT).

In the Application below, we first fit the most relaxed variants of each of the three generic models. In this fitting process, we treated each preparation time (Cue-Target Interval) by Paradigm combination as a separate “replication” of the basic design.

Application: comparing task switching in WHERE and WHAT tasks

In this section we present our CARIS modeling of a particular study in which we compared switching in two different cuing paradigms. For the sake of brevity, we do not report the experiment in full (see Yehene & Meiran, 2007). The participants in the study were 95 college students: about half of each gender. They were tested on two cuing task-switching paradigms with identical logical structure, block structure, and trial structure (see Fig. 1). The first paradigm was object-based and it involved a SQUARE-CIRCLE task cued by the Hebrew equivalent of the word SHAPE and a SMALL-LARGE task, cued by the Hebrew word for SIZE. These tasks were performed on the four combinations of these values (small-circle, large-circle, small-square, large-square). Two keys on the lower row of the keyboard were used for response collection.

The second paradigm was spatial, a paradigm used by Meiran, Gotler, and Perlman (2001, Experiment 1). It involved switching between two location tasks: UP-DOWN

and RIGHT-LEFT. Both tasks were performed on the same set of target stimuli: The four positions within a 2×2 grid. These tasks were cued in advance by two instructional cues: arrows pointing sideways indicated the RIGHT-LEFT task while arrows pointing upward and downward indicated the UP-DOWN task. The responses were two keys on the numeric keypad, the position of which were compatible with the nominal categories they indicated. The upper-left key indicated UP and LEFT while the lower-right key indicated DOWN and RIGHT. Half of the participants used this key-setup, while the other half used the upper-right key and the lower-left key.

Participants were tested on the spatial paradigm in Session 1 and on the object paradigm in Session 2. Previous, unpublished studies from our lab indicated that there is no carryover of practice effects between these two paradigms (Sosna, 2001). Each session began with 20 warmup mixed-tasks trials, followed by four identical mixed-tasks blocks of 80 trials each, and ending with a single block of instructed single-task (80 trials). The task chosen for that block was counterbalanced. Each trial consisted of an inter-trial interval of 1,500 ms. Previous studies using the spatial paradigm indicated that inter-trial intervals longer than 0.5 s are ineffective in reducing switch cost (Meiran, Chorev, & Sapir, 2000; Meiran, Levine, Meiran, & Henik, 2000; Meiran et al., 2001). During the inter-trial interval, either the screen was empty (the object paradigm) or an empty grid was presented (the space paradigm). It was followed by an instructional cue presented for either a short (100 ms) or a long (1,000 ms) CTI, followed by the target stimulus presented along with the instructional cue until the response was given.

The results obtained in the two paradigms were very similar. Although there were some significant interactions with Paradigm, in most cases, these interactions explained a negligible fraction (less than 2%) of the effect-variance. There was one exception, the interaction between Paradigm and CTI, which showed a relatively large difference between the paradigms in the short CTI. Aside from this interaction, the pattern of significant highest-order interactions was the same in both paradigms. There was a triple interaction between Task-Switch, Response-Repetition and Cue-Target Interval and a two-way interaction between Task-Switch and Congruency. When the Cue-Target Interval was short, we observed a facilitatory response repetition effect in repeat trials, a reversed response repetition effect in switch trials and a null effect in single-task trials. This interaction was considerably flatter when the Cue-Target Interval was long. In addition, switch cost and mixing cost were larger in the incongruent condition than in the congruent condition (see Fig. 7).

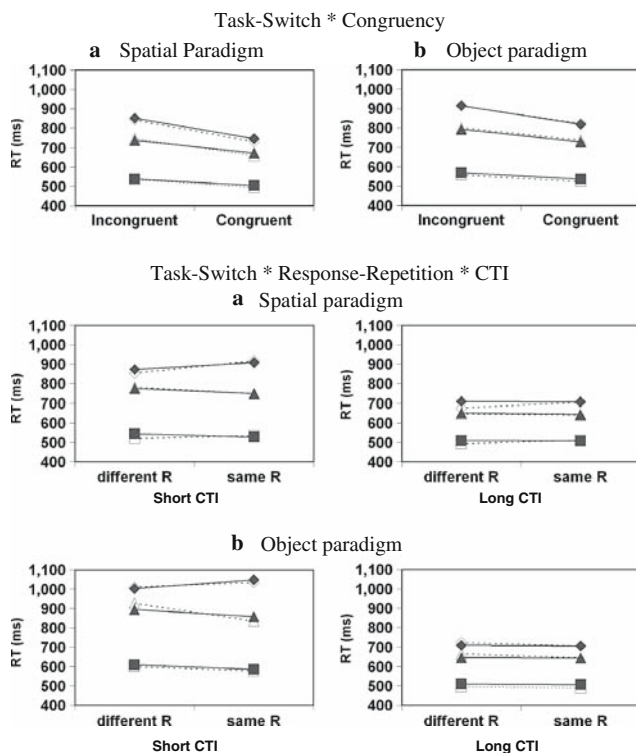


Fig. 7 Actual (dashed line) and reproduced (solid line) mean RT according to Model 1–2 (diamond switch, triangle repeat, square single). *We depict the two highest order interactions that were found to be significant in the ANOVAs. CTI cue-target interval

Modeling

The 48 RT means in the design [Paradigm (2) × CTI (2) × Switch (3, switch, repeat, single-task) × Congruency (2) and Response Repetition (2)] were first compared in a one-way repeated measures ANOVA, yielding a significant result, $F(47, 4,418) = 147.29$, $MSe = 18,331.35$, $p < 0.0001$. This (admittedly trivial) finding indicates that there was a significant amount of variance among the 48 means to be explained by the models. For the sake of modeling, we considered the 48 conditions as four replications of 12 basic conditions. The 12 basic conditions were formed by the factorial combination of Task-Switch (switch, repeat, single-task), Congruency (congruent, incongruent), and Response Repetition (same or different response than in Trial $n - 1$). These 12 conditions were repeated in each CTI and in each Paradigm.

Model choice

Modeling was performed by minimizing the sum of square differences between the actual mean RT and the predicted mean RT, using Microsoft ExcelTM Solver routine. As recommended by Lorch and Myers (1990), we fitted the data of individual participants, meaning that the parameter

values were allowed to differ between participants. We began with the most relaxed variants of the three generic models. These relaxed variants were formed by allowing all the parameters to differ between the four replications (namely, there was a separate parameter set for each CTI and Paradigm condition). The parameters included the core parameters: w_I , w_A and w_{CR} , as well $w_{I-SINGLE}$ or $w_{A-SINGLE}$, depending on whether it was Model 1 or Model 2, and additional parameters: D_{MIX} and D_{SWITCH} , $RS-Rate$ and $RT-Intercept$. In using the search algorithm to fit these models, we decided to use bounds that limit the possible parameter values. Such an approach was needed because we modeled individual participants' data, which were not very stable, and because of the complexity of the model. The bound we used were chosen to ensure that the selected parameter values would be realistic. Specifically, the core parameters were all allowed to vary between 0 and 1. In addition, the parameters representing willed control, w_I (Models 1 and 3) and w_A (Models 2 and 3) had to be above 0.50 (otherwise the wrong task would have been executed, which we knew to be wrong based on the low error rates). The parameters representing perseveration, w_I (Models 2) and w_A (Model 1) had to be above 0.50 because values below 0.50 do not indicate perseverative tendencies. In fact, a value below 0.50 implies that executing Task A in Trial $n - 1$ resulted in a bias in favor of Task B.

Because we fitted the results of individual participants, we obtained three model-fit indices. One was the number of participants for whom a given model produced the best fit. The second was the R^2 value between the mean predicted values (across participants) and the mean observed value (across participants), and the final one was the Root-Mean-Square Deviation (RMSD) in ms, again between the mean predicted value and the mean observed value. Before comparing the models, it is important to mention the fact that the models did not have the same number of free parameters. Specifically, in Model 3, neither w_I nor w_A were determined by Task $n - 1$, and therefore Model 3 did not include a separate instantiation of any of the parameters for the single-task condition. As a result, (the relaxed variants of) Models 1 and 2 had 32 free parameters for each participant (8 parameters for each of the 4 “replications”) and Model 3 had only 28 free parameters for each participant (7 parameters for each of the 4 “replications”). For that reason, we also considered the relative fit of the models in the mixed-tasks conditions, separately, because the number of free parameters was the same for all models for these conditions. Before reporting the results, we would like to emphasize the fact that the number of free parameters, 32 or even 28, is obviously excessive. Therefore, we did not focus on the degree of model fit per-se, which is inflated due to the number of free parameters. Instead, the focus was on the *relative* fit of the three models, because

the goal in this analytic stage was to choose a generic model. Only after we chose a generic model, we were able to considerably reduce the number of free parameters.

The modeled data set included 95 (participants) \times 48 (conditions) = $4,560$ data points. The fit results indicate an $R^2 = 0.993, 0.986,$ and $0.983,$ for Models 1, 2 and 3, respectively. These R^2 values represent the fit between the mean predicted RT and the mean observed RT (thus removing individual participants' related variance). All these values are very high but they do not indicate a clear advantage for any particular model. A clearer picture emerged when we considered the four combinations of CTI and Paradigm, separately. Table 1 presents the R^2 data as well as the percentage of participants whose data were best fit by a given model for the different CTI and Paradigm conditions. As can be seen in Table 1, Model 1 best fit the short CTI results, which was true for both paradigms, while Model 2 best fit the long CTI results in both paradigms. These differences in model fits are most apparent when considering the percentage of participants whose results were best fit by a given model. By chance, a third of the participants are expected to be best fit by any given model. The numbers significantly deviated from this expectancy, $\chi^2_{(2)} = 49.76, 29.87, 60.24,$ and $66.32,$ all $ps < 0.000001,$ for spatial short-CTI, object short-CTI, spatial long-CTI and object, long CTI, respectively. The fact that Model 3 was unsuccessful cannot be attributed to the smaller number of free parameters, because the picture remained essentially unchanged when only the mixed tasks

conditions were considered, for which the number of free parameters was the same for the three models. Based on these results, we endorsed Model 1–2, which was identical to Model 1 in the short CTI and identical to Model 2 in the long CTI.

A relaxed variant of Model 1–2 was fit to the data in a preliminary run. Because we estimated the parameters for individual participants, we were able to compare them against critical values using t -tests (see Lorch & Myers, 1990). These critical values were zero (for $w_{CR}, D_{MIX}, D_{SWITCH}, RS\text{-Rate}$ and *Corrected RT-Intercept*), 0.50 (for the parameters representing a bias in favor of Task $n - 1,$ namely, w_A for the short CTI and w_1 for the long CTI), and 1 (for the set parameters dictated by the current task, namely w_1 for the short CTI and w_A for the long CTI). In addition, we compared parameters in the four “replications” for equality again using standard Paradigm \times CTI ANOVAs and t -tests performed on the parameter estimates of individual participants. These preliminary analyses allowed us to impose equality constraints on some parameters and to eliminate others, so that we were eventually left with 18 free parameters, which were used in the final fit of Model 1–2 (see Table 2)² The 18 parameters that were eventually left in the model were all (a) significantly different from the relevant comparison level (zero, $.50,$ 1.0); (b) where applicable, significantly different between “replications”.

The resultant 18-parameter model yielded an $R^2 = 0.990,$ with an RMSD = 17 ms (for the mean observed vs. mean predicted analysis). This R^2 value is underestimated relative to R^2 values often reported in the literature. The reason is that it describes the fit of the mean predicted RT across participants to the mean observed RT. In many cases, authors generate a single set of predicted values and fit it against the group means. When Model 1–2 was fit in this manner, its R^2 value was increased to $0.991.$ The R^2 value we obtained is in the very upper range, and the RMSD value (17 ms) is in the very lower range of the values reported by other modelers including Logan and Bundesen (2003), Schneider and Logan (2005), and Sohn and Anderson (2001). Figure 7 presents the mean RTs predicted by Model 1–2 against the actual means. The figure depicts only the two high-order interactions which were found to be significant in both paradigms in the standard ANOVAs.

² In comparison, the number of significant degrees of freedom (including the intercept term) in the standard 5-way ANOVA was 21 (actually almost 22 because of an additional parameter with $p = 0.059$). To determine these numbers we needed to break down the 2-*df* Switch variable into orthogonal contrast. The contrasts were switch cost: switch vs. repeat, and mixing cost: switch + repeat vs. single task. This was done for the main effect of Switch and all the interactions involving Switch).

Table 1 Model fit (R^2) and the proportion of participants whose results were best fitted by a given model (%N)

Model		Condition			
		Short CTI		Long CTI	
		Spatial	Shape	Spatial	Shape
All conditions					
1	R^2	0.995	0.990	0.986	0.984
	% N	67.4	57.9	27.4	14.7
2	R^2	0.979	0.976	0.983	0.993
	% N	14.7	12.6	68.4	72.6
3	R^2	0.972	0.980	0.959	0.980
	% N	17.9	29.5	4.2	12.6
Mixed tasks only					
1	R^2	0.989	0.943	0.976	0.918
	% N	66.3	57.9	25.3	15.8
2	R^2	0.897	0.853	0.954	0.983
	% N	10.5	12.6	65.3	72.6
3	R^2	0.933	0.918	0.932	0.910
	% N	23.2	29.5	9.5	11.6

CTI Cue-target interval

Table 2 Parameter estimates for the chosen Model 1–2 (with 18 free parameters)

Parameter	Description	Mean value	95% Confidence interval	# Reached the bound
w_1 —spatial short CTI	Weight given to the relevant stimulus dimension in Trial n	0.932	0.919–0.945	8 $\chi^2_{(1)} = 65.69$
w_1 —object short CTI	Weight given to the relevant stimulus dimension in Trial n	0.954	0.945–0.963	9 $\chi^2_{(1)} = 62.41$
w_A —spatial short CTI	Weight given to what was the relevant action representation in Trial $n - 1$	0.540	0.520–0.559	30 $\chi^2_{(1)} = 12.89$
w_A —object short CTI	Weight given to what was the relevant action representation in Trial $n - 1$	0.512	0.506–0.517	57 $\chi^2_{(1)} = 3.80$, NS
$w_{A-SINGLE}$ short CTI both paradigms	Weight given to what was the relevant action representation in Trial $n - 1$ (single-task)	0.691	0.662–0.720	Spatial 1 $\chi^2_{(1)} = 91.04$ object 1 $\chi^2_{(1)} = 91.04$
w_A long CTI both paradigms	Weight given to the relevant action representation in Trial n	0.920	0.897–0.943	Spatial 7 $\chi^2_{(1)} = 69.06$ object 0
w_I long CTI both paradigms	Weight given to the relevant stimulus dimension from Trial $n - 1$	0.533	0.515–0.551	Spatial 32 $\chi^2_{(1)} = 10.12$ object 13 $\chi^2_{(1)} = 50.12$
$w_{I-SINGLE}$ long CTI both paradigms	Weight given to the relevant stimulus dimension from Trial $n - 1$ (single-task)	0.664	0.625–0.703	Spatial 10 $\chi^2_{(1)} = 59.21$ object 5 $\chi^2_{(1)} = 76.05$
w_{CR} —both CTIs both paradigms	A change in weight in favor of the representation related to the response executed in Trial $n - 1$	0.022	0.017–0.027	Spatial-short 26 $\chi^2_{(1)} = 19.46$ spatial-long 32 $\chi^2_{(1)} = 10.12$ object-short $\chi^2_{(1)} = 69.06$ object-long 7 $\chi^2_{(1)} = 69.06$
D_{SWITCH} —spatial short CTI	Unexplained switch cost (cue repetition effect)	37 ms	22–51 ms	
D_{SWITCH} —object short CTI	Unexplained switch cost (cue repetition effect)	68 ms	44–91 ms	
D_{SWITCH} —long CTI (both paradigms)	Unexplained switch cost (cue repetition effect)	12 ms	3–31 ms	
D_{MIX} —spatial short CTI	Unexplained mixing cost (task decision time)	84 ms	52–115 ms	
D_{MIX} —object short CTI and long CTI in both paradigms	Unexplained mixing cost (task decision time)	57 ms	36–77 ms	
$RS-Rate$ —spatial short CTI	Response selection rate	368 ms/ Str. unit	310–427 ms/ Str. unit	
$RS-Rate$ —object short CTI	Response selection rate	511 ms/ Str. unit	458–563 ms/ Str. unit	
$RS-Rate$ —long CTI (both paradigms)	Response selection rate	277 ms/ Str. unit	228–326 ms/ Str. unit	
Corrected $RT-Intercept$ (both CTIs, both paradigms)	Predicted RT without response selection (time taken for shallow stimulus encoding and response preparation)	301 ms	254–349 ms	

CTI cue-target interval. “# reached the bound” represents the number of participants (out of 95) for whom the chosen parameter had a value identical with the imposed a-priori bound. See text for details

In order to test the statistical significance of the deviation of the model from the data, we compared the observed and predicted RTs using Source (observed vs. predicted) as an independent variable in ANOVAs (see Altmann, 2006). Because this test appears to have excessive statistical power, we ran an additional analysis on a group of randomly selected 20 participants and note when a given

effect was significant also for this smaller group. Indeed, significant effects that did not pass this criterion were very small, sometimes as small as 3 ms.

In the first stage, we conducted an ANOVA with Source and Condition as within-participant variables, with Condition having 48 levels corresponding to the factorial combination of all the experimental variables. This single

test was conducted to control for Alpha inflation due to multiple comparisons. The interaction between Source and Condition reached significance, indicating a significant discrepancy between the predicted and the observed results, $F(47,4418) = 3.85$, $MSe = 3,593.32$. This was true also when the analysis was performed on 20 participants.

In the next phase, we tried to probe the source of the discrepancy between predicted and observed RTs by conducting more focused comparisons. This was achieved by replacing Condition with the five independent variables (Paradigm, CTI, Task-Switch, Congruency and Response-Repetition). Three interactions involving Source reached statistical significance even when we analyzed the results of 20 participants. These include the three-way interactions between Source, Congruency and CTI, $F(1,94) = 19.19$, $MSe = 1,363.21$, Source, Task-Switch and Response-Repetition, $F(2,188) = 25.16$, $MSe = 2,256.13$, and Source, Paradigm and Response-Repetition, $F(1,94) = 58.75$, $MSe = 3,424.86$.

These significant effects reflect the fact that (a) there was a small observed reduction in the Congruency effect as a result of increasing the CTI (from 75 to 70 ms), which was non-significant. However, the predicted pattern indicated a sharper reduction (from 76 to 57 ms); (b) there was a significant interaction between the Switch-Repeat contrast and Response Repetition reflecting a reversed response repetition effect in the switch condition (25 ms) and a facilitatory effect in the repeat condition (38 ms), whereas the predicted pattern was less sharp (19 and 17 ms, respectively). This pattern is caused by the fact that the model does not predict an interaction between Switch and Response Repetition in the long CTI, whereas such an interaction was found. The 4-way interaction, which reflects this trend reached significance in the full analysis, $F(2,188) = 5.51$, $MSe = 2,157.79$, but did not reach significance when the ANOVA was performed on the results of 20 participants; Finally (c) the Response-Repetition effect was reversed in the observed RT and not in the predicted RT for the spatial paradigm, -14 versus 3 ms respectively, $F(1,94) = 26.93$, $MSe = 3,382.46$, and was larger in the observed than in the predicted RT for the object paradigm, 23 versus 4 ms, respectively, $F(1,94) = 27.51$, $MSe = 4,019.46$.

Several additional interactions were significant but only when the entire sample was analyzed and not when the analysis was performed on the small group. These include the four-way interaction between Source, Congruency, Response-Repetition and CTI, $F(1,94) = 5.39$, $MSe = 2,010.98$; the three-way interaction between Source, Paradigm and Congruency, $F(1,94) = 8.08$, $MSe = 3,249.97$; and two-way interactions between Source and Task-Switch, $F(2,188) = 13.71$, $MSe = 2,505.72$, and Source and Congruency, $F(1,94) = 9.84$, $MSe = 1,914.41$.

In summary, although the predicted RTs differed significantly from the observed RTs, the discrepancies, by and large, were relatively small. Moreover, the model was able to generate the qualitative replicable patterns of results, and failed, at occasions in predicting patterns that seem to be unique to the present experiment such as the triple interaction between Congruency, Response Repetition and CTI that was observed here, not usually observed, and not predicted by the model (see Pitt, Kim, Navarro, & Myung, 2006). Finally, the level of fit exhibited by the present model is, in most cases better, and certainly not worse than that of other models of task switching in the literature.

Implications of the chosen parameter values

Table 2 presents the mean parameter values across participants along with their 95% confidence intervals. In some cases, using confidence intervals to examine if a parameter value differs from 0, 1 or 0.50 was problematic because of the a-priori bounds imposed on the parameters. For this reason, we used another method to test whether the parameters are different from the critical value. In this method we checked the number of participants for whom the estimated parameter value has reached the a-priori bound (0.5 or 1). We further reasoned that if the true parameter value was (a) equal to the bound and (b) the parameter distribution was symmetrical, one would predict that for 50% of the participants, the estimated parameter would hit the a-priori bound. Based on this line of reasoning, we used χ^2 tests to examine if the actual number of participants whose estimated parameter hit the a-priori bound was significantly different from the predicted 50%. As the rightmost column of Table 2 shows, the conclusions were the same as those reached when considering confidence intervals. Here we list the implications of the chosen parameter values:

1. The corrected *RT-Intercept* had a value close to the typical simple RT. The fact that we obtained similarly reasonable values in four replications (CTI \times Paradigm) provides important validation to the modeling process.
2. The parameters representing control (w_1 for the short CTI, w_A for the long CTI) had very high values, but still values that were significantly different than unity. The reason for that is that, if they had a value of 1, the congruency effect would have been eliminated in the predicted results, as seen when their values were manually changed to unity (see Fig. 8a). One interpretation of this result is in terms of control failure. Namely, the best selection is represented by a parameter value of 1, and smaller values show that this

best level of performance was not achieved. Another interpretation which we believe to be more plausible is that it may not be beneficial to focus too narrowly on one piece of information, when the other piece of information may soon become relevant (Goschke, 2000). Specifically, perfect selection on say size-related information would be very beneficial in executing the SIZE task. However, the SIZE task is performed in conditions where the SHAPE task is also performed. Keeping an “open window” for shape-related information may therefore be beneficial in these situations.

3. The parameters representing a bias in favor of Task $n - 1$ were significantly higher than 0.50, showing that such a bias existed. As can be seen in Fig. 8b, the small but significant deviation from 0.50 was critical to fully reproduce the Switch by Congruency interaction.
4. w_{CR} had a value significantly higher than zero, suggesting that executing a given response led to a binding of that response (and/or related stimuli) with the given task-dependent interpretation. This value was essential to reproduce the interactions involving Switch and Response-Repetition, as seen in Fig. 8c.
5. The parameters dictated by Task $n - 1$ had higher values in the single-task condition than in the mixed tasks condition, which explained a considerable portion of the mixing cost. As can be seen in Fig. 8d, when the parameters in the single-task condition were manually changed to the value chosen for the mixed tasks condition, the predicted RT for the single-task condition was substantially higher than the observed RT.
6. The unexplained switch cost was significantly larger than zero, and importantly, was smaller given a long preparation time. The preparation-related reduction in the unexplained switch cost was 25 ms in the spatial paradigm (37–12 ms) and 56 ms in the object paradigm (68–12 ms).
7. The unexplained mixing cost was also significantly larger than zero. It was reduced by preparation in the spatial paradigm (from 84 to 57 ms) but not in the object paradigm (57 ms for both CTIs). According to our interpretation, these parameters represent the time taken to make a task choice.
8. The *RS-Rate* was larger when the CTI was short than when it was long, which indicates a generally more efficient response selection given optimal preparation (Hackley & Valle Inclan, 1998, 1999, see also Meiran & Chorev, 2005).
9. Paradigm content dictated the parameter values in the short CTI condition but not in the long CTI condition.

Validation study

To validate our choice of Model 1–2, we ran an additional experiment on 31 participants who performed the Shape–Size paradigm using task cues that provided the category–response mapping directly (e.g., “SQUARE CIRCLE”). The paradigm was otherwise identical to that modeled earlier. We reasoned that the new cues would either reverse the results to fit Model 2–1 (Model 2 for the short CTI and Model 1 for the long CTI) instead of Model 1–2 or at least would shift the proportion of best-fit participants in this direction. Note that one could argue that the dimensional cues (e.g., SHAPE) that were used by Yehene and Meiran (2007) conveyed less information than the mapping cues that were used in the validation study. We argue that this criticism is incorrect given the fact that the same pair of task cues was used throughout the experiment, so that the information provided by the cue (after the cue has been processed) was which one of two cues was currently in effect.

The results supported our predictions. Specifically, the proportion of participants whose results fitted Model 2 in the short CTI (11 out of 31, 35%) increased relative to the results modeled earlier (Yehene & Meiran, 2007, Shape–Size results; 12 out of 95, 13%) when category–response cues were used. Concomitantly, the proportion of participants whose results fitted Model 1 ($15/31 = 48\%$) decreased relative to the results of Yehene and Meiran ($55/95 = 58\%$). This change in proportions was significant, $\chi^2(1) = 5.99$. In the long CTI, the proportion of participants whose results fitted Model 2 ($15/31 = 48\%$) decreased relative to the results of Yehene and Meiran ($69/95 = 72\%$). Concomitantly, the proportion of participants whose results fitted Model 1 increased ($9/31 = 29\%$) relative to the results of Yehene and Meiran ($14/95 = 15\%$). This change in proportions was also significant, $\chi^2(1) = 4.70$. The present results provide important validation to our interpretation of the model as well as to model choice. Specifically, they are consistent with the interpretation that dimensional cues (e.g., SHAPE) such as those used in the experiment of Yehene and Meiran (2007), modeled before, initially attract attention to the input, and attention is drawn to action representation only later, because this information is derived or retrieved rather than more directly available. Mapping cues (e.g., such as those used in the validation study, “SQUARE CIRCLE”) attract attention initially to action representation, and only later attention is drawn to the input dimension, because in this case, this information is derived. The fact that the mapping cues only shifted the proportions in the predicted direction rather than reversing them could be explained by the fact

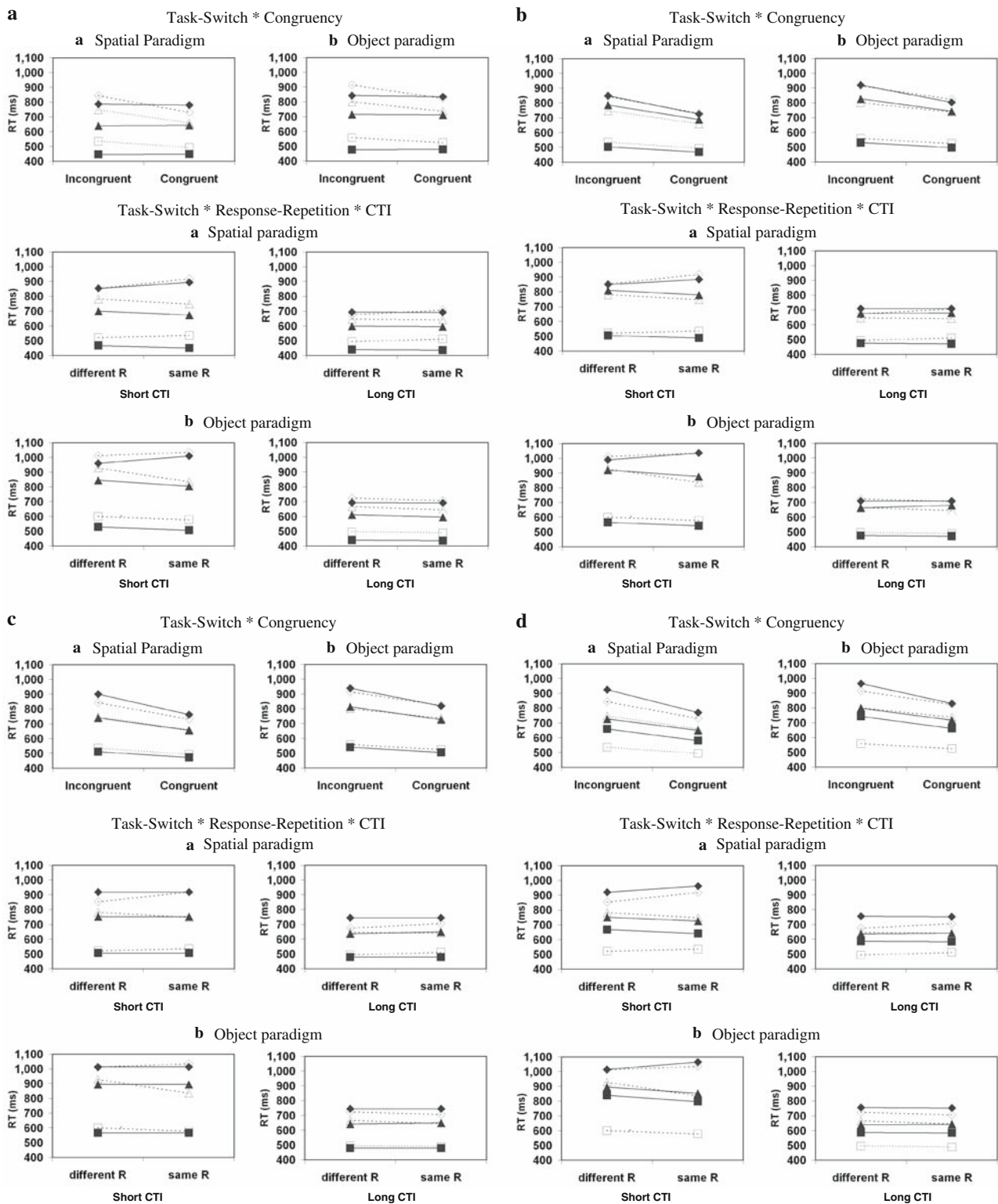


Fig. 8 Exploring the contribution of the model's parameters. Actual (dashed line) and reproduced (solid line) mean RT according to Model 1–2 (diamond switch, triangle repeat, square single), **a** with the parameter w_I manually changed to 1.00 in the short CTI and the parameter w_A manually changed to 1.00 in the long CTI; **b** with the parameter w_I manually changed to 0.50 in the long CTI and the

parameter w_A manually changed to 0.50 in the short CTI; **c** with the parameter w_{CR} manually changed to zero; **d** with the parameter $w_{I-SINGLE}$ manually changed to the estimate of w_I in the long CTI and the parameter $w_{A-SINGLE}$ manually changed to the estimate of w_A in the short CTI; CTI cue-target interval

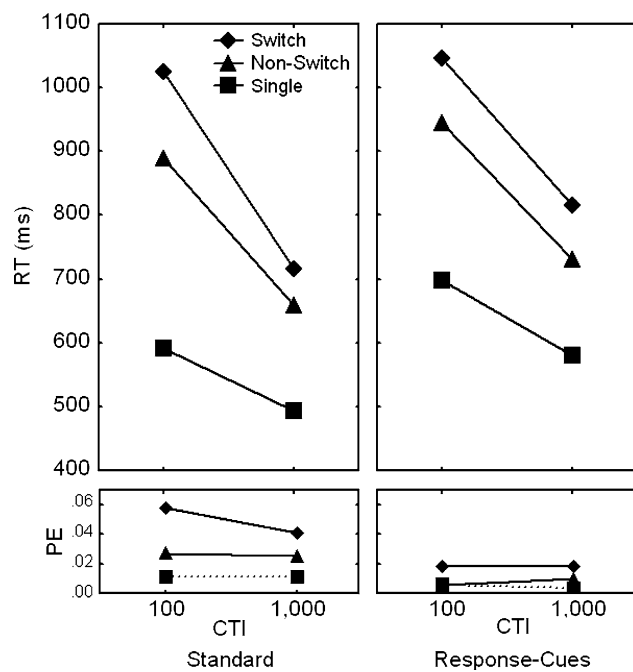


Fig. 9 Mean RT according to CTI, Switch and Experiment (Yehene & Meiran, 2007, shape-size results, $N = 95$, who used dimension cues vs. the validation experiment with category-response cues). CTI cue-target interval

that the cue was visual, regardless of its type, which in itself attracts attention to the input. Alternatively, input selection may be a more flexible function than action representation. Diamond's (1985) A not B results hint in this direction because looking (which is input selection) was not perseverative while the action of reaching was perseverative.

We also compared the mean Shape-Size RT results from Yehene and Meiran (2007) (the results which were modeled here, based on dimension cues) to the new experiment involving the same tasks but with category-response cues. The triple interaction between Switch, CTI and Experiment was significant, $F(2, 252) = 10.59$, $MSe = 2811.99$ (Fig. 9). It reflected the fact that when category-response cues were used, switch costs did not decline significantly with increasing CTI, $F < 1$, for the simple interaction between CTI and Switch in the new experiment, while such a trend was found for dimension cues, $F(1, 126) = 62.93$, $MSe = 2447.31$, for the simple interaction between CTI and Switch conducted on the results of Yehene and Meiran. These results fully confirm the results of Mayr and Kliegl (2000) in our paradigm.

CARIS account of RT distribution and error rates

CARIS, as described so far, does not deal with RT distributions and error rates. The present section is added to

show that, while this aspect of CARIS is admittedly underdeveloped, CARIS is not inherently limited in this respect.

To account for RT distributions and error rates we ran a simulation study. In this study, we concentrated on the spatial paradigm because the two paradigms yielded very similar results. We simulated 10,000 trials per each of the 24 conditions. Specifically, in each "trial" the value of the core (w_I , w_A , w_{CR}) CARIS parameters was randomly chosen by sampling them from their respective distributions (see subsequently). For simplicity sake, the remaining parameters were taken from Table 2 and were constant. All these parameter values, when entered into the CARIS equations, uniquely determined the simulated RT. This process was repeated, generating simulated RT distributions. Note that the simulated RTs vary between trials because w_I , w_A , w_{CR} varied between trials in the simulation. Because the chosen model was different for the two CTI conditions we ran two separate simulations, one based on Model 1 (for the short CTI) and one based on Model 2 (for the long CTI).

To randomly choose CARIS core parameters, it was important to make a-priori assumptions concerning their distributions. The assumptions that we adopted were that the values of the Task n control parameters (w_I for Model 1, w_A for Model 2) vary exponentially. We used the exponential function because it is the simplest special case of the Weibull function, used to model failures and unreliability. Here, a failure implies imperfect selection according to the instructed task. Although the Weibull function is often used to model accumulated failure as a function of time (which does not apply in the present case), this is not always the case, and the Weibull function is used to model failure that accumulates over other domains as well (e.g., Zhao, 2005). The parameter determined by T_{n-1} (w_A for Model 1, w_I for Model 2) was assumed to be distributed normally, with a mean as in Table 2. Because w_{CR} was practically bounded at zero (meaning that its distribution cannot be symmetric), we assumed that it too, was distributed exponentially.

Errors and task choice

CARIS assumes that errors result from two reasons. One is that there was an error in the choice of the task vector. This point is elaborated in greater detail later. The other reason why errors occur is the fact that, in some trials, the values of parameter(s) which are determined by Task $n - 1$ ("inner obstacle") exceed that of the control parameter (those chosen based on Task n). Specifically, in CARIS, response selection is based on a competition between the correct response and the incorrect response. In congruent trials, no such competition exists because the irrelevant stimulus dimension activates the correct response.

Figure 10 depicts the simulation of the short CTI condition. Figure 10a presents the univariate distribution of simulated trials according to their w_I and w_A values. As can be seen, w_I tends to be larger than w_A , but in some cases, w_A is larger than w_I . If this is a switch incongruent trial, this means that the potency of the wrong response is higher than that of the correct response, resulting in an error³. Figure 10b presents the bivariate distribution of simulated trials according to w_I and w_A . It depicts the trials in which $w_I > w_A$, and a correct response is chosen (marked as “+” and occupying the upper left side of Fig. 10b) and the trials in which $w_A > w_I$ (and the wrong response is chosen in incongruent-switch trials. These trials are marked as “.” And they occupy the lower right side of Fig. 10b).

As mentioned previously, errors may result from choosing the wrong task vector, representing “task errors”. Meiran and Daichman (2005), who used Multinomial Processing Tree modeling (Riefer & Batchelder, 1988) to explain the error rates in the presently studied spatial paradigm, showed that these rates are best explained by a model assuming (among other things) that participants occasionally execute the wrong task (see further Steinhauser & Hübner’s, 2006). Importantly, Meiran and Daichman showed that the rate of “task errors” increased in the switch condition relative to the repeat condition, and this switch effect was eliminated in the long CTI condition. Therefore, in simulating the short

CTI condition, we assumed that, on a randomly chosen 0.05 of the switch trials, the wrong task was chosen.

In each of the two simulations (one for the short CTI, the other for the long CTI), we manually varied three values until a reasonable fit to the observed results was observed. These included the parameter of the exponential functions (Lambdas), and the Sigma of the normal distribution. This variation was done under the constraint that the mean parameter value would remain the same as the estimated mean⁴. Figure 11 presents the simulated RT distributions and Table 3 presents the mean simulated error rates. The observed RT distributions were computed after forcing the mean RTs of individual participants to equal the sample mean. This adjustment was needed to compensate for the fact that the simulation did not involve individual differences. As can be seen in Fig. 11 and Table 3, the simulation generates RT distributions and error rates that are quite similar to those we observed. Note again that the observed results are just an approximation partly because they are *not* taken from a single participant, who was tested over many sessions, but are an aggregate (after equating mean RT across participants) of many participants who performed the paradigms only for a short period of time.

General discussion

In the present study, we presented CARIS, which is a modeling framework for task-switching experiments. Our results led us to endorse a particular CARIS model. Below we discuss the implications of the modeling results, explain how the chosen model explains the observed RT effects, compare the model to other models in the literature, discuss the limitations of the present work, and discuss the broader implications for cognitive control.

Implications of the chosen model

We chose Model 1–2, which is a hybrid model that, as elaborated before, is best interpreted as reflecting reactive control rather than proactive control. Unlike proactive control, which is based on setting the system in advance to perform a given task, reactive control is based on online biasing which takes into account the changing context (task goal). CARIS Model 1–2 is unique in that it proposes that

³ Specifically, response selection is based on a competition between the correct response and the incorrect response. In congruent trials, no such competition exists because the irrelevant stimulus dimension activates the correct response. Competition arises in incongruent trials because the irrelevant stimulus dimension activates a competing response. Correct responding in these trials therefore depends on the fact that the correct response is more potent than the incorrect response. Without loss of generality, let us consider a special case in which the two response keys are: $R_{A(LARGE-CIRCLE)} = (1 \ 0 \ 1 \ 0)$ and $R_{B(SMALL-SQUARE)} = (0 \ 1 \ 0 \ 1)$ and an incongruent target, say, $S_{LARGE-SQUARE} = (1 \ 0 \ 0 \ 1)$. Let us assume further that the task is SIZE. In such a case, the correct response is R_A (the target is LARGE). The potency for that response according to Model 1 is either $w_S \cdot w_R$ in the case of a task repetition or $w_S \cdot (1 - w_R)$ in the case of a task switch. The potency of the competing response R_B is $(1 - w_S) \cdot (1 - w_R)$ in the case of a task repetition and $(1 - w_S) \cdot w_R$ in the case of a task switch. For R_A to be chosen, the following inequality must hold: $P_{Response-A} > P_{Response-B}$. Replacing $P_{Response-A}$ and $P_{Response-B}$ with their values, as defined above shows that the inequality translates into $w_S > (1 - w_R)$ for task repetitions and into $w_S > w_R$ for task switches. The competition between the two responses becomes even stronger in the case of a response repetition, where w_A is replaced by $w_A + w_{CR}$. Less formally, the processing strategy represented by Model 1 ensures correct responding by a strong-enough input selection that overcomes the counterproductive adjustment of action representation. Similarly, Model 2 strategy ensures correct responding by a strong enough bias in the action representation which counteracts the counterproductive adjustment in input selection.

⁴ Because the exponential distribution has only one parameter, Lambda, this parameter dictates both the variance ($1/\text{Lambda}^2$) and the mean value ($1/\text{Lambda}$). Having decided to maintain the mean value the same as that estimated (Table 2) could have implicated that we could not vary the distribution to enable better fit to the data. To allow more freedom there, we changed Lambda and added a constant so that the variance could change without changing the mean.

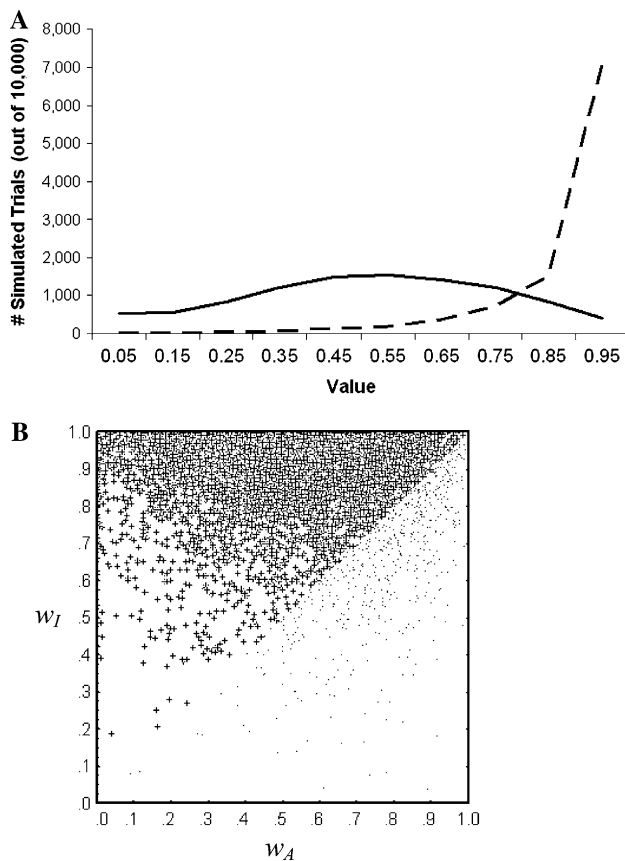


Fig. 10 The w_A and w_I values used to simulate RT in the Short CTI. For the correct response to be selected, w_I (which is determined by the task in Trial n) should exceed w_A (which is determined by the task in Trial $n - 1$). **a** Uni-variate distributions, w_I dashed line, w_A solid line; **b** bi-variate distribution (errors appear on the lower-right corner, where $w_I < w_A$). See text for details

different pieces of cue-related information are used for control depending on the amount of time allowed for advance preparation. It is suggested that the processing of task cues initially attracts attention to either the input or the action. When more time is allowed for cue processing, other (inferred or retrieved) information attracts attention to the other aspect of response selection. The portion of the response selection apparatus on which the current control bias operates depends on the current focus. With dimensional cues such as SHAPE, control first operates on the input end. Biasing of action representation takes place only later, after the related information was retrieved. These points are demonstrated in Fig. 12. The fact that the I-Set and the A-Set were very rarely controlled simultaneously (Model 3) suggests that they cannot be controlled simultaneously, reflecting some kind of an attentional bottleneck, perhaps. We cannot rule out the possibility that under favorable conditions and perhaps more appropriate task cues, such parallel control may take place nevertheless.

Aside from the model fit and the results of the validation study, it is interesting to see if there are additional sources of evidence for the plausibility of Model 1–2. A recent imaging study seems to provide evidence that is at least compatible with our conclusions. Specifically, Ruge et al. (2005) studied the spatial paradigm that was employed here in an event-related functional magnetic resonance imaging study. Their results show that brain areas which showed an oxygen consumption switch-related increase when the cue-target interval was short did not show this increase when the interval was long. Additionally, there was no switch-related activity during the preparatory interval, only when the target was presented that such an activity was observed. Finally, both switch trials and repeat trials involved the activation of portions of the pre-frontal—parietal network known from other studies to be involved in task switching. Although Ruge et al. endorsed a different interpretation, CARIS Model 1–2 is compatible with them. We suggest that the network activated by both switch and repeat trials represents task decision, whereas the switch-specific activation represent the transient control bias required to overcome perseverative tendencies. The presence of task-decision related activity in the long CTI in the absence of evidence for temporary biasing is incompatible with models which assume proactive control because task decision should complete before task implementation. The fact that temporary biasing was evident only in the short CTI is explained by the fact that Model 1 prevails in that interval. Furthermore, because the control strategy that this model represents is relatively ineffective there was a greater demand for top-down effort, as reflected in the activation in regions believed to be involved in implementing such control. When the top-down biasing strategy was effective (the long cue target interval, where Model 2 prevails), lesser control effort was involved in implementing it.

Subsequently, we discuss how Model 1–2 explains the RT effects that were listed in the Introduction.

Task switch cost

Model 1–2 explains switch cost in the cuing paradigm as a result of two processes. First, regardless of preparation time, some aspect of the task set is perseverative (based on Task $n - 1$) rather than instruction-based (Task n); namely, the switch cost was determined, in part, by a task-set carryover effect (Allport et al., 1994; Allport & Wylie, 2000; Meiran, 1996, see also Yeung, et al., 2006). The second contribution to switch cost is an inserted processing stage, represented by D_{SWITCH} , which was larger in the short CTI condition than in the long CTI condition. This inserted processing stage is possibly responsible for cue-repetition effects as discussed by Logan and Bundesen (2003) and Mayr and Kliegl (2003).

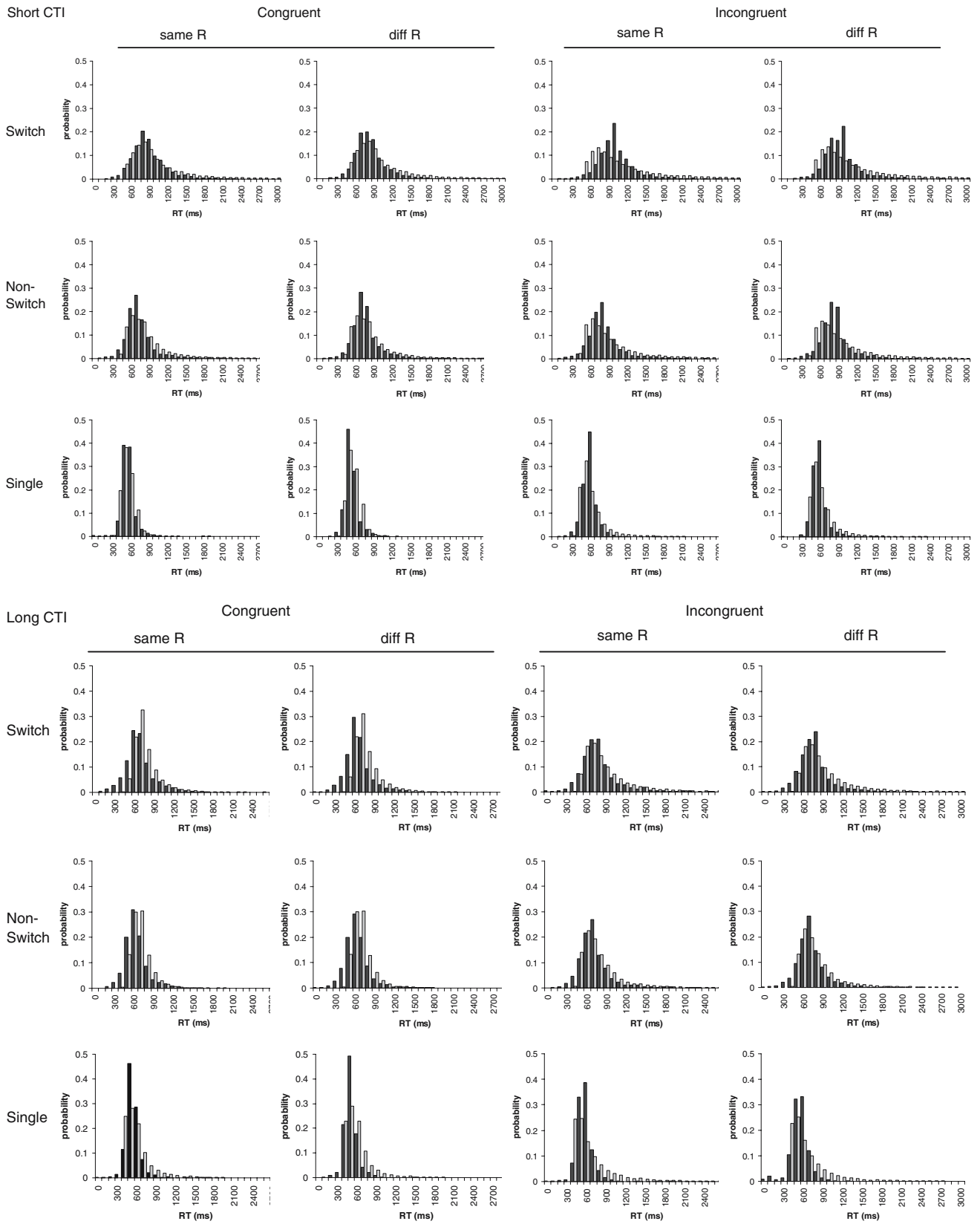


Fig. 11 Simulated (*gray*) and Observed (*black*) RT distributions-spatial paradigm. *CTI* cue-target interval

Table 3 Observed (and predicted, in brackets) proportions of errors—spatial paradigm

	Response–Repetition	Congruent		Incongruent	
		Switch	Non-switch	Single	Switch
Short CTI	Same	0.00 (0.01)	0.01 (0.01)	0.01 (0.00)	0.08 (0.11)
	Different	0.02 (0.00)	0.00 (0.02)	0.00 (0.00)	0.10 (0.11)
Long CTI	Same	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.05 (0.06)
	Different	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.06 (0.06)

CTI cue-target interval. Across condition Pearson correlation between observed and predicted is $r = 0.92$

Task mixing cost

Mixing cost is explained by two processes. One is captured by D_{MIX} and the other is captured by the CARIS core. As mentioned before, D_{MIX} is interpreted as the time taken to make the task decision, which is made more complicated given the bivalent stimuli that we used (see Rubin & Meiran, 2005, for direct support). The other process is reflected in the fact that action representation (in the short CTI) and input selection (in the long CTI) was more strongly biased in single-tasks conditions than in mixed-tasks conditions. Note that in mixed-tasks conditions, a bias according to the $n - 1$ st task is productive in repeat trials but counterproductive in switch trials, in which the bias is in favor of the wrong task. In contrast, in single-task trials, the bias is always productive because the n th and $n - 1$ st tasks are always the same in single-task blocks. This single-mixed difference could reflect one of the two processes: A consistent accumulation of updating over trials permitted in single-task conditions or an increased task commitment in single-task conditions (e.g., see Monsell, Sumner, & Waters, 2003, for the concept of task commitment).

Preparation

Preparation is a widely discussed topic in the task-switching literature (see Meiran, 2008a; Monsell, 2003, for reviews). CARIS Model 1–2 provides an account for preparation as well. Preparation had a general facilitatory effect in the mixed tasks conditions and it also reduced switch cost. Model 1–2 explains these effects by three factors. First, preparation reduced switch costs as explained already. Second, preparation had a general facilitatory effect on the *RS-Rate*, indicating faster response-selection in the prepared state. Finally, D_{MIX} and D_{SWITCH} were decreased with increasing CTI in some conditions.

Reduction of switch cost in the long cue-target interval

This effect is explained both by a reduction in the unexplained switch cost and by the change in strategy (Model 2 vs. Model 1). The reduction in the unexplained switch cost supports our interpretation of the D_{SWITCH} parameter as reflecting cue processing time. The present modeling

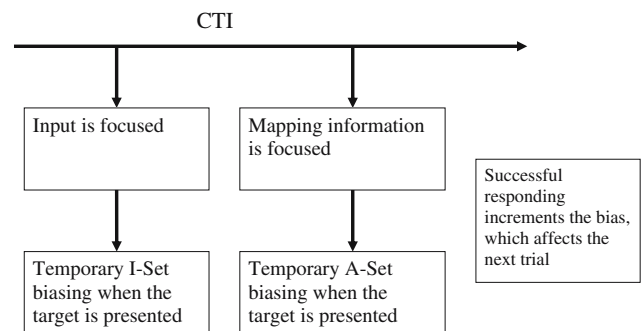


Fig. 12 Description of the hypothesized sequence of events when the task cue indicates the relevant stimulus dimension (e.g., SHAPE). Cue processing first attracts attention to the relevant dimension and then the extracted category-response mapping (e.g., CIRCLE → right key press) information attracts attention to action representation. Top-down biasing takes place when the target is presented. The type of biasing (I-Set or A-Set) is dictated by the currently attended information. Successful responding increments the default control parameter in the direction of the $n - 1$ st Task. CTI cue-target interval

results therefore provide an interesting piece of converging evidence that cue processing time contributes to switch costs (Logan & Bundesen, 2003; Mayr & Kliegl, 2003).

The fact that Action-Set based control (Model 2) represents a more efficient strategy than an Input-Set based control (Model 1) is supported by Mayr and Kliegl's (2000) who showed smaller switch costs (given short preparation time) with mapping cues than with dimensional cues. Our validation study confirms these results in the present paradigm. Note that Mayr and Kliegl interpreted their results in terms of an inserted processing stage involving the retrieval of the category-response mapping information. Accordingly, the switch costs observed in the short CTI were interpreted as being increased because of the extra time needed to retrieve this mapping information. Our interpretation is quite different. According to us, the larger switch costs observed in the short CTI result, in part, from the fact that correct responding is possible even without adopting the appropriate (Trial n) A-Set, but the price paid is a larger switch cost.

Congruency

The congruency effect is due, to a large extent, to the less than perfect input selection coupled with the almost

unbiased action representation (short CTI); as well as the less than perfect action-representation coupled with an almost unbiased input selection (long CTI). As a result of these two features (imperfect control-based selection and a nearly unbiased learning-based selection) irrelevant stimulus information can enter response selection. In congruent trials, this activation facilitates responding because the two types of information, relevant and irrelevant, are linked to the same response. In incongruent trials, the relevant information makes the correct response potent, whereas the irrelevant information makes the wrong response potent. The consequent response competition is reflected in slowing. The increased congruency effect in switch trials results from the greater emphasis given to the $n - 1$ st task in the parameters representing perseveration. This, in turn, increases the potency of wrong responses and weakens the potency of the correct response.

Response repetition

The results indicated a facilitatory response repetition effect in repeat trials, a reversed effect in switch trials. Model 1–2 explains these effects by w_{CR} , which changes the action representation in favor of the $n - 1$ st task. It therefore increases the bias in favor of the correct representation in repeat trials but decreases this bias in switch trials.

Action-related effects not explicitly modeled

Broadly speaking, the action-related effects not explicitly modeled are qualitatively compatible with Model 1–2 as explained later. The reduction or even elimination of switch effects following stop trials is explained by the fact that responding (Philipp et al., 2007) or response activation (Hübner & Druet, 2006) is necessary to establish a default bias in favor of Task $n - 1$. Moreover, if the response is made according to the wrong task rule, the default bias accord with this (wrong) rule, which results in the reversal of the switch effect (Steinhauser & Hübner, 2006). The larger switch effect found with bivalent response setups (Mayr, 2001; Meiran, 2000b) is explained by the fact that, when the response setup is univalent, the category-response mapping is consistent and is not modified by task switching. As we have shown earlier, the change in action representation is a major contributor to the switch cost, which also explains why a change in response meaning is associated with a cost (Meiran & Marciano, 2002).

A recent paper by Dreisbach, Goschke, and Haider (2006) provides an interesting challenge to our conclusions. This study compared conditions in which the participants were given stimulus-response instructions to

conditions in which the same stimuli and responses were involved but were instructed in task switch terms. Switch costs were found only when task switching was instructed but congruency effects were found regardless of the instructions. We simulated the performance in the condition with S-R rule instructions in the spatial paradigm, by using the chosen parameters from Table 2 and by introducing the following changes to these parameters. We assumed that D_{SWITCH} to be zero (no conscious task decision taking place). In addition, the default bias in favor of the $n - 1$ st Task was greatly reduced, assuming that the conscious focusing on this task contributes to the formation of a bias in favor of Task $n - 1$. w_{CR} was set at zero for similar reasons. With the following set of simulated parameters ($w_{I-Short} = 0.95$, $w_{A-Short} = 0.502$, $w_{I-Long} = 0.505$, $w_{A-Long} = 0.95$), switch cost became negligible, 6 and 12 ms in the short and long cue-target interval, respectively, but the congruency effect remained substantial as in the study of Dreisbach et al., 82 and 62 ms, respectively. Although this simulation is only suggestive, it points to an interesting and non-trivial implication that being conscious of the task contributes to perseveration, presumably because it helps consolidating the bias in favor of that task after its execution.

Limitations, potential extensions and future directions

An apparent limitation is that CARIS had been applied to tasks involving what may be crudely defined as perceptual classification. We argue that the limitation is more apparent than real because CARIS can potentially deal with semantic classification (Sudevan & Taylor, 1987) and episodic memory retrieval (Mayr & Kliegl, 2000) as well. For example, in switching between HIGH-LOW (than 5) and ODD-EVEN tasks, the description of the stimuli could be based on ordered vectors like (*high low odd even*).

Interestingly, the above does not hold for Stroop task switching (e.g., Allport et al., 1994). It seems that CARIS may not be able to account for this kind of switching because task control in this case cannot be based on choosing between different response-categories (Input-Set), because these categories are the same for the two tasks (color names). Similarly, selective action representation cannot be applied because the mapping of categories to overt responses is the same for both tasks. Evidence that Stroop task switching is a special case is the fact that this form of switching appears to be necessary to generate a phenomenon called “switch asymmetry” (Allport et al., 1994; Yeung & Monsell, 2003a, 2003b). This phenomenon refers to the larger switch cost that is observed in the easier task. Another case in which switch asymmetry is found is in language switching (Meuter & Allport, 1999). In that

study, input selection was disabled because the stimuli (Arabic digits) were univalent, they had one dimension only (their value). Action representation was also disabled as a control strategy because there was no overlap between the responses. Switching between compatible and incompatible spatial responding (e.g., De Jong, 1995) also produces switch asymmetry and for similar reasons.

There are three additional true limitations. First, while we acknowledged the fact that task decision and cue encoding are time-consuming processes, CARIS only estimates their duration and does not truly explain them. Other models are better developed to deal with these issues (e.g., Altmann & Gray, 2002; Logan & Bundesen, 2003). Second, we examined two extreme cue-target intervals. Given our choice of Model 1-2, an intriguing possibility is that performance in intermediate cue-target intervals is characterized by a mixture of trials involving Model 1 and Model 2 strategy. This idea is very similar to De Jong's (2000) idea in which switch costs sometimes represent a mixture of fully prepared and fully unprepared trials. A final limitation is that, at present, CARIS does not account for backward inhibition (Mayr & Keele, 2000), namely slowed switch trials involving returning to a just-abandoned task. This limitation is mentioned partly because backward inhibition has been shown to be related to action (Gade & Koch, 2007b; Philipp et al., 2007; Schuch & Koch, 2003).

Comparison to Meiran's (2000a) model

CARIS builds on Meiran's (2000a) model in several respects and the two models share core assumptions such as graded selection, the description of the response selection process as composed of two components, which are independently controlled and several key features of the formalism. This, however, is where the similarity ends. Unlike its predecessor, CARIS (a) has an explicit inclusion of task decision; (b) includes residual, unexplained switch cost and mixing cost; (c) involves the generalization to three competing models and hybrids; (d) has improved inferential statistics—most notably, being able to test the model's lack of fit and statistical testing on the model's parameters; (e) involves an explicit representation of category-response binding effects as opposed to implied representation in Meiran (2000a); (f) allows testing of core assumptions. For example, Meiran's model is closest to the present Model 1, while here we contrasted Model 1 with Models 2 and 3; (g) CARIS suggests an account for RT distributions and error rates. Most importantly, Model 1–2 that we endorsed supports reactive control, whereas Meiran's model assumes proactive control. Accordingly, the present account of preparation effects on switch costs is drastically different than that offered by Meiran.

Comparison to other models

There are already quite a few formal models explaining task switching. Each one of these models emphasizes different phenomena. Probably the phenomena that attracted most of the attention of modelists are preparation and switching effects (Badre & Wagner, 2006; De Jong, 2000; Gilbert & Shallice, 2002; Logan & Bundesen, 2003; Rubinstein, et al. 2001; Schneider & Logan, 2005; Sohn & Anderson, 2001; Yeung & Monsell, 2003a). In addition, Altmann and Gray (2002) modeled phenomena related to goal forgetting. Only four of the existing models in the literature explain the action-related effects that we mentioned: congruency (Gilbert & Shallice, 2002; Schneider & Logan, 2005; see also Brown, Reynolds, & Braver, 2007) and Response-Repetition (Brown et al.; Kleinsorge & Heuer, 1999). To the best of our knowledge, no model had so far attempted to explain switching, preparation, and action-related effects on mean RT, RT distributions and error rates, all within the same framework (which also implicates that it explains the various interactions among these variables). We wish to mention a recent connectionist model by Badre and Wagner (2006) that seems to resemble CARIS in some respects. Namely, the link between stimuli and responses is mediated by conceptual categories. Moreover, task execution results in incremental changes in the pattern of connectivity within the network, and the role of control is in overcoming these carryover effects. It remains to be shown whether this model can account for preparation and action-related effects.

Implications for cognitive control

The present work suggests some principles which bear implications to cognitive control in general:

1. Task execution requires setting up the values of control parameters. Switch costs are observed when these parameters change. While we focused on input selection within a sensory modality and action representation, there are additional parameters such as those involving sensory modality change (Quinlan & Hill, 1999), response modality (Philipp & Koch, 2005), and the sequence of sub-tasks (Luria & Meiran, 2003, 2006). This means that, at least at some level, there is no such thing as a task set or a schema. Instead, "task sets" represent ad-hoc configurations of control parameters.
2. Task execution (possibly, only partial execution, see Hübner & Druwey, 2006) causes perseverative tendencies. It creates a default bias in favor of the executed task.

3. The role of online control is to counteract these carryover effects.
4. Online control is accomplished by information selection.

Acknowledgments The research was supported by a grant to the first author from the Israel Science Foundation. We thank Thomas Goschke, Thomas Kleinsorge, Erik Altmann, Iring Koch and an anonymous reviewer for their insightful and challenging comments, and Rotem Eren-Rabinovich for English proofreading.

References

- Ach, N. (2006). *On volition* (T. Herz, Trans.). (Original work published 1910) Retrieved from University of Konstanz, Cognitive Psychology Web site: <http://www.uni-konstanz.de/kogpsych/ach.htm>.
- Allport, A., Styles, E. A., & Hsieh, S. (1994). Shifting intentional set: Exploring the dynamic control of tasks. In: C. Umiltà, & M. Moscovitch (Eds.), *Attention and Performance XV: Conscious and Unconscious Processing* (pp. 421–452). Cambridge, MA: MIT Press.
- Allport, A., & Wylie, G. (2000). ‘Task-switching’, stimulus-response bindings and negative priming. In: S. Monsell, & J. Driver (Eds.), *Attention and Performance XVIII: Control of Cognitive Processes* (pp. 35–70). Cambridge, MA: MIT Press.
- Altmann, E. M. (2006). Task switching is not cue switching. *Psychonomic Bulletin & Review*, *13*, 1016–1022.
- Altmann, E. M. (2007). Comparing switch costs: Alternating runs and explicit cuing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*, 475–483.
- Altmann, E. M., & Gray, W. D. (2002). Forgetting to remember: The functional relationship of decay and interference. *Psychological Science*, *13*, 27–33.
- Arrington, C. M., Logan, G. D., & Schneider, D. W. (2007). Separating cue encoding from target processing in the explicit task cuing procedure. Are there “true” task switch effects? *Journal of Experimental Psychology: Learning, Memory, & Cognition*, *33*, 484–502.
- Badre, D., & Wagner, A. D. (2006). Computational and neurobiological mechanisms underlying cognitive flexibility. *PNAS*, *103*, 7186–7191.
- Brass, M., Ruge, H., Meiran, N., Rubin, O., Koch, I., Zysset, S., Prinz, W., & von Cramon, D. Y. (2003). When the same response has different meaning: Recoding the response meaning in the lateral prefrontal cortex. *NeuroImage*, *20*, 1026–1031.
- Braver, T. S., Reynolds, J. R., & Donaldson, D. I. (2003). Neural mechanisms of transient and sustained cognitive control during task switching. *Neuron*, *39*, 713–726.
- Brown, J. W., Reynolds, J. R., & Braver, T. S. (2007). A computational model of fractionated conflict-control mechanisms in task switching. *Cognitive Psychology*, *55*, 37–85.
- Campbell, K. C., & Proctor, R. W. (1993). Repetition effects with categorizable stimulus and response sets. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *19*, 1345–1362.
- De Jong, R. (1995). Strategic determinants of compatibility effects with task uncertainty. *Acta Psychologica*, *88*, 187–207.
- De Jong, R. (2000). An intention-activation account of residual switch costs. In: S. Monsell, & J. Driver (Eds.), *Attention and Performance XVIII: Control of Cognitive Processes* (pp. 357–376). Cambridge, MA: MIT Press.
- De Pisapia, N., & Braver, T. S. (2006). A model of dual control mechanisms through anterior cingulate and prefrontal cortex interactions. *Neurocomputing*, *69*, 1322–1326.
- Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*, 193–222.
- Diamond, A. (1985). Development of the ability use to recall to guide action, as indicated by infant’s performance on AB. *Child Development*, *56*, 868–883.
- Dreisbach, G., Goschke, T., & Haider, H. (2006). Implicit task sets during task switching? *Journal of Experimental Psychology: Learning, Memory and Cognition*, *32*, 1221–1233.
- Fagot, C. (1994). *Chronometric investigations of task switching*. Unpublished PhD Thesis, University of California, San Diego.
- Fey, E. T. (1951). The performance of young schizophrenics and young normals on the Wisconsin Card Sorting Test. *Journal of Consulting Psychology*, *15*, 311–319.
- Gade, M., & Koch, I. (2007a). Cue-task associations in task switching. *The Quarterly Journal of Experimental Psychology*, *60*, 762–769.
- Gade, M., & Koch, I. (2007b). The influence of overlapping response sets on task inhibition. *Memory & Cognition*, *35*, 603–609.
- Gilbert, S. J., & Shallice, T. (2002). Task switching: A PDP model. *Cognitive Psychology*, *44*, 297–337.
- Goschke, T. (2000). Intentional reconfiguration and involuntary persistence in task-set switching. In: S. Monsell, & J. Driver (Eds.), *Attention and Performance XVIII: Control of Cognitive Processes* (pp. 331–355). Cambridge, MA: MIT Press.
- Hackley, S. A., & Valle-Inclan, F. (1998). Automatic alerting does not speed late motoric processes in a reaction-time task. *Nature*, *391*, 786–788.
- Hackley, S. A., & Valle-Inclan, F. (1999). Accessory stimulus effects on response selection: Does arousal speed decision making? *Journal of Cognitive Neuroscience*, *11*, 321–329.
- Hintzman, D. L. (1986). “Schema abstraction” in a multiple-trace memory model. *Psychological Review*, *93*, 411–428.
- Hoffmann, J., Kiesel, A., & Sebald, A. (2003). Task switches under go/nogo conditions and the decomposition of switch costs. *European Journal of Cognitive Psychology*, *15*, 101–128.
- Hommel, B. (1993). Inverting the Simon effect by intention: Determinants of direction and extent of effects of irrelevant spatial information. *Psychological Research*, *55*, 270–279.
- Hommel, B., Müsseler, J., Aschersleben, G., & Prinz, W. (2001). The theory of event coding (TEC): A framework for perception and action planning. *Behavioral and Brain Sciences*, *24*, 849–937.
- Hübner, R., & Druwey, M. (2006). Response execution, selection, or activation: What is sufficient for response-related repetition effects under task shifting? *Psychological Research*, *70*, 245–261.
- Kleinsorge, T. (1999). Response repetition benefits and costs. *Acta Psychologica*, *103*, 295–310.
- Kleinsorge, T., & Heuer, H. (1999). Hierarchical switching in a multi-dimensional task space. *Psychological Research*, *62*, 300–312.
- Koch, I. (2005). Sequential task predictability in task switching. *Psychonomic Bulletin & Review*, *12*, 107–112.
- Koch, I., & Allport, A. (2006). Cue-based preparation and stimulus-based priming of tasks in task switching. *Memory & Cognition*, *34*, 433–444.
- Koch, I., & Philipp, A. M. (2005). Effects of response selection on the task-repetition benefit in task switching. *Memory & Cognition*, *33*, 624–634.
- Lavie, N. (1995). Perceptual load as a necessary condition for selective attention. *Journal of Experimental Psychology: Human Perception and Performance*, *21*, 451–468.
- Loehlin, J. C. (1987). *Latent variable models: An introduction to factor, path, and structural analysis*. Hillsdale, NJ: Erlbaum.
- Logan, G. D., & Bundesen, C. (2003). Clever homunculus: Is there an endogenous act of control in the explicit task-cuing procedure? *Journal of Experimental Psychology: Human Perception and Performance*, *29*, 575–599.

- Logan, G. D., & Gordon, R. D. (2001). Executive control of visual attention in dual-task situations. *Psychological Review*, *108*, 393–434.
- Lorch, R. F., & Myers, J. L. (1990). Regression analysis of repeated measures data in cognitive research. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *16*, 149–157.
- Los, S. A. (1996). On the origin of mixing costs: Exploring information processing in pure and mixed blocks of trials. *Acta Psychologica*, *94*, 145–188.
- Luria, R., & Meiran, N. (2003). Online order control in the psychological refractory period paradigm. *Journal of Experimental Psychology: Human Perception and Performance*, *29*, 556–574.
- Luria, R., & Meiran, N. (2006). Dual route for subtask order control: Evidence from the Psychological Refractory Period paradigm. *Quarterly Journal of Experimental Psychology: Section A*, *59*, 720–744.
- Mayr, U. (2001). Age differences in the selection of mental sets: The role of inhibition, stimulus ambiguity, and response-set overlap. *Psychology and Aging*, *16*, 96–109.
- Mayr, U., & Bryck, R. L. (2005). Sticky rules: integration between abstract rules and specific actions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*, 337–350.
- Mayr, U., & Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. *Journal of Experimental Psychology: General*, *129*, 4–26.
- Mayr, U., & Kliegl, R. (2000). Task-set switching and long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *26*, 1124–1140.
- Mayr, U., & Kliegl, R. (2003). Differential effects of cue changes and task changes on task-set selection costs. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *29*, 362–372.
- Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *22*, 1423–1442.
- Meiran, N. (2000a). Modeling cognitive control in task-switching. *Psychological Research*, *63*, 234–249.
- Meiran, N. (2000b). The reconfiguration of the stimulus task-set and the response task set during task switching. In: S. Monsell, & J. Driver (Eds.), *Attention and Performance XVIII: Control of Cognitive Processes* (pp. 377–400). Cambridge, MA: MIT Press.
- Meiran, N. (2005). Task rule congruency and Simon-like effects in switching between spatial tasks. *Quarterly Journal of Experimental Psychology: Section A*, *58A*, 1023–1041.
- Meiran, N. (2008a). Task switching: Mechanisms underlying rigid vs. flexible self control. In: R. Hassin, K. Ochsner, & Y. Trope (Eds.) *Social Cognition and Social Neuroscience*, NY: Oxford University Press (in press).
- Meiran, N. (2008b). The dual implication of dual affordance: Stimulus-task binding and attentional focus changing during task preparation. *Experimental Psychology*. doi: [10.1027/1618-3169.55.4.252](https://doi.org/10.1027/1618-3169.55.4.252).
- Meiran, N., & Chorev, Z. (2005). Phasic alertness and the residual task-switch cost. *Experimental Psychology*, *52*, 109–124.
- Meiran, N., Chorev, Z., & Sapir, A. (2000). Component processes in task switching. *Cognitive Psychology*, *41*, 211–253.
- Meiran, N., & Daichman, A. (2005). Advance task preparation reduces task error rate in the cueing task-switching paradigm. *Memory and Cognition*, *33*, 1272–1288.
- Meiran, N., Gotler, A., & Perlman, A. (2001). Old age is associated with a pattern of relatively intact and relatively impaired task-set switching abilities. *The Journals of Gerontology: Series B: Psychological Sciences and Social Sciences*, *56B*, 88–102.
- Meiran, N. & Kessler, Y. (2008). The task rule congruency effect in task switching reflects activated long term memory. *Journal of Experimental Psychology: Human Perception and Performance*, *34*, 137–157.
- Meiran, N., Levine, J., Meiran, N., & Henik, A. (2000). Task set switching in schizophrenia. *Neuropsychology*, *14*, 471–482.
- Meiran, N., & Marciano, H. (2002). Limitations in advance task preparation: Switching the relevant stimulus dimension in speeded same-different comparisons. *Memory & Cognition*, *30*, 540–550.
- Meuter, R. F. I., & Allport, A. (1999). Bilingual language switching in naming: Asymmetrical costs of language selection. *Journal of Memory and Language*, *40*, 25–40.
- Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*, 167–202.
- Milner, B. (1964). Some effects of frontal lobectomy in man. In: J. M. Warren, & K. Akert (Eds.), *The Frontal Granular Cortex and Behavior* (pp. 313–334). New York: McGraw-Hill.
- Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*, 134–140.
- Monsell, S., & Mizon, G. A. (2006). Can the task cuing paradigm measure an “endogenous” task set reconfiguration process? *Journal of Experimental Psychology: Human Perception and Performance*, *32*, 493–516.
- Monsell, S., Sumner, P., & Waters, H. (2003). Task-set reconfiguration with predictable and unpredictable task switches. *Memory and Cognition*, *31*, 327–342.
- Norman, D. A., & Shallice, T. (1986). Attention to action: Willed and automatic control of behavior. In: R. J. Davidson, G. E. Schwartz, & D. Shapiro (Eds.) *Consciousness and self-regulation: Advances in research and theory* (Vol. 4, pp. 1–18). New York: Plenum.
- Pashler, H. (1991). Shifting visual attention and selecting motor responses: Distinct attentional mechanisms. *Journal of Experimental Psychology: Human Perception and Performance*, *17*, 1023–1040.
- Pashler, H., & Baylis, G. (1991). Procedural learning: 2. Intertrial repetition effects in speeded-choice tasks. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *17*, 33–48.
- Philipp, A. M., Jolicœur, P., Falkenstein, M., & Koch, I. (2007). Response selection and response execution in task switching: Evidence from a go-signal paradigm. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *33*, 1062–1075.
- Philipp, A. M., & Koch, I. (2005). Switching of response modalities. *Quarterly Journal of Experimental Psychology A: Human Experimental Psychology*, *58A*, 1325–1338.
- Piaget, J. (1954). *The construction of reality in the child*. New York: Basic Books.
- Pitt, M. A., Kim, W., Navarro, D. J., & Myung, J. I. (2006). Global model analysis by parameter space partitioning. *Psychological Review*, *113*, 57–83.
- Quinlan, P. T., & Hill, N. I. (1999). Sequential effects in rudimentary auditory and visual tasks. *Perception & Psychophysics*, *61*, 375–384.
- Riefer, D. M., & Batchelder, W. H. (1988). Multinomial modeling and the measurement of cognitive processes. *Psychological Review*, *95*, 318–339.
- Rogers, R. D., & Monsell, S. (1995). The cost of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General*, *124*, 207–231.
- Rubin, O., & Meiran, N. (2005). On the origins of the task mixing cost in the cuing task switching paradigm. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*, 1477–1491.
- Rubinstein, J. S., Meyer, D. E., & Evans, J. E. (2001). Executive control of cognitive processes in task switching. *Journal of*

- Experimental Psychology: Human Perception and Performance*, 27, 763–797.
- Ruge, H., Brass, M., Koch, I., Rubin, O., Meiran, N., & von Cramon, D. Y. (2005). Advance preparation and stimulus induced interference in cued task switching: Further insights from BOLD fMRI. *Neuropsychologia*, 43, 340–355.
- Ruthruff, E., Remington, R. W., & Johnston, J. C. (2001). Switching between simple cognitive tasks: The interaction of top-down and bottom-up factors. *Journal of Experimental Psychology: Human Perception and Performance*, 27, 1404–1419.
- Schneider, D. W., & Logan, G. D. (2005). Modeling task switching without switching tasks: A short-term memory priming account of explicitly cued performance. *Journal of Experimental Psychology: General*, 134, 343–367.
- Schuch, S., & Koch, I. (2003). The role of response selection for inhibition of task sets in task shifting. *Journal of Experimental Psychology: Human Perception and Performance*, 29, 92–105.
- Schuch, S., & Koch, I. (2004). The cost of changing the representation of action. *Journal of Experimental Psychology: Human Perception and Performance*, 30, 566–582.
- Shalev, L., & Algom, D. (2000). Stroop and Garner effects in and out of Posner's beam: Reconciling two conceptions of selective attention. *Journal of Experimental Psychology: Human Perception and Performance*, 26, 997–1017.
- Sohn, M. H., & Anderson, J. R. (2001). Task preparation and task repetition: Two-component model of task switching. *Journal of Experimental Psychology: General*, 130, 764–778.
- Sosna, G. (2001). *Practice and transfer in task-switching: The effect of quantity and frequency of switching*. Unpublished MA Thesis, Ben-Gurion University of the Negev, Beer-Sheva.
- Steinhauser, M., & Hübner, R. (2006). Response-based strengthening in task-shifting: Evidence from shift effects produced by errors. *Journal of Experimental Psychology: Human Perception and Performance*, 32, 517–534.
- Sudevan, P., & Taylor, D.A. (1987). The cueing and priming of cognitive operations. *Journal of Experimental Psychology: Human Perception and Performance*, 13, 89–103.
- Treisman, A.M. (1969). Strategies and models of selective attention. *Psychological Review*, 76, 282–299.
- Verbruggen, F., Liefoghe, B., Szmalec, A., & Vandierendonck, A. (2005). Inhibiting responses when switching: Does it matter? *Experimental Psychology*, 52, 125–130.
- Verbruggen, F., Liefoghe, B., & Vandierendonck, A. (2006). Selective stopping in task switching: The role of response selection and response execution. *Experimental Psychology*, 53, 48–57.
- Ward, L. M. (1982). Determinants of attention to local and global features of visual forms. *Journal of Experimental Psychology: Human Perception and Performance*, 8, 562–581.
- Waszak, F., Hommel, B., & Allport, A. (2003). Task-switching and long-term priming: Role of episodic stimulus-task bindings in task-shift costs. *Cognitive Psychology*, 46, 361–413.
- Woodward, T. S., Meier, B., Tipper, C., & Graf, P. (2003). Bivalency is costly: Bivalent stimuli elicit cautious responding. *Experimental Psychology*, 50, 233–238.
- Yehene, E., & Meiran, N. (2007). Is there a general task switching ability? *Acta Psychologica*, 126, 169–195.
- Yehene, E., Meiran, N., & Soroker, N. (2005). Task alternation cost without task alternation: Measuring intentionality. *Neuropsychologia*, 43, 1858–1869.
- Yehene, E. & Meiran, N., & Soroker, N. (2008). Basal ganglia play a unique role in task switching within the frontal-sub-cortical circuits: Evidence from patients with focal lesions. *Journal of Cognitive Neuroscience*. doi:10.1162/jocn.2008.20077.
- Yeung, N., & Monsell, S. (2003a). Switching between tasks of unequal familiarity: The role of stimulus-attribute and response-set selection. *Journal of Experimental Psychology: Human Perception and Performance*, 29, 455–469.
- Yeung, N., & Monsell, S. (2003b). The effects of recent practice on task switching. *Journal of Experimental Psychology: Human Perception and Performance*, 29, 919–936.
- Yeung, N., Nystrom, L. E., Aronson, J. A., & Cohen, J. D. (2006). Between-task competition and cognitive control in task switching. *The Journal of Neuroscience*, 26, 1429–1438.
- Zelazo, P. D., & Frye, D. (1997). Cognitive complexity and control: A theory of the development of deliberate reasoning and intentional action. In: M. Stamenov (Ed.), *Language structure, discourse, and the access to consciousness* (pp. 113–153). Amsterdam & Philadelphia: John Benjamins.
- Zhao, J-H. (2005). A probabilistic mechanics approach to die cracking prediction in flip-chip ball grid array package. *IEEE Transactions on Components and Packaging*, 28, 390–396.