

Modelling cognitive control in task switching and ageing

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In an attempt to better understand the reasons for old-age effects on task switching performance, we fitted a quantitative model (Meiran, 2000a) to results from an experiment comparing young and elderly participants. Modelling results indicate that the most pronounced effect of old age was in what can be broadly defined as the duration of the response selection. In addition, compared to young participants, the elderly tended to rely on learning from the preceding trial, which improved their performance in single-task conditions but impaired it when the tasks switched frequently. Relatively modest effects of old age were found in the ability to selectively attend to the task relevant stimulus dimension and on the duration of processing stages preceding or following response selection.

Old age is known to affect cognitive functioning. Physiological evidence (e.g., Raz, Gunning-Dixon, Head, Dupuis, & Acker, 1998) and neuropsychological evidence (e.g., West, 1996) suggest that old age most strongly affects the frontal lobes. Since the frontal lobes are commonly believed to be involved in cognitive control, a reasonable conjecture is that old age has an especially large influence on cognitive control functioning. Along this line, we examined the influence of age on task-switching performance, which is commonly believed to reflect control functioning. Specifically, we applied a model of task switching we have developed (Meiran, 2000a, b; Meiran, Chorev, & Shapir, 2000a; Meiran, Levine, Meiran, & Henik, 2000b) in an effort to interpret old-age effects on task-switching performance. The model has two aspects. The first aspect refers to the fractio-

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nation of task-alternation cost into components. In this paper, we provide only a short description of this aspect of the model. A more complete treatment of the literature on the differential effects of old age on the various components may be found in Meiran, Gotler, and Perlman (in press). The second aspect is more central here and refers to a processing model, which describes the underlying processes involved in task switching performance and enables one to estimate the relevant process parameters based on empirical results. In the present paper we used this model in an attempt to gain a better understanding of the pattern of old-age effects in task switching performance.

A MODEL OF TASK SWITCHING: STUDIES ON NORMAL YOUNG ADULTS

Components of alternation cost

Task switching often produces a sizeable decrement in performance (e.g., Allport, Styles, & Hsieh, 1994; De Jong, 2000; Gopher, Armony, & Greenshpan, 2000; Jersild, 1927; Los, 1999; Mayr & Keele, 2000; Meiran, 1996, 2000a, b; Meiran, Chorev, & Sapir, in press; Rogers & Monsell, 1995). Following Goschke (2000), Los (1999), and Rogers and Monsell (1995), we argue that task switching affects several component processes. One approach to identifying the component processes involved in task switching was suggested by Fagot (1994). In order to identify the components, Fagot distinguished between three experimental conditions. In explaining these conditions, we will mark each trial in a sequence by the task being performed, Task A (e.g., colour discrimination) or Task B (e.g., shape discrimination). The first condition is (1) *single task* (AAA ..., BBB ...); the second condition involves trials immediately following a task switch in mixed-tasks blocks (*switch trials*, e.g., ABBAB); and the third condition involves task repetition trials in mixed task blocks (*nonswitch trials*, e.g., ABBAB). Usually, the best performance is found in the single-task condition; the worst performance is found in switch trials. Thus, the difference between reaction time (RT) in single task conditions versus switch trials reflects the joint contribution of all component processes and is termed *alternation cost*. Alternation cost is decomposed into two large components: *mixing cost* (nonswitch RT minus single task RT) and *switching cost* (switch RT minus nonswitch RT).

Fagot (1994) decomposed switching cost into two subcomponents that are similar to what we call preparatory cost and residual cost (see later). Later, we (Meiran, Chorev, & Sapir, 2000) identified a third subcomponent, dissipating cost. To do so, we employed the cueing version of the

task-switching paradigm. In that paradigm, trials involving the various tasks are ordered randomly, and each trial begins with instructions telling participants which task to execute. Instructions are conveyed by means of symbolic cues. Using instructional cues allowed us to manipulate two intervals. One, the response-cue interval (RCI), is the interval following the response in Trial N-1, when the participant waits for the instructional cue in Trial N. RCI is unlikely to be used for active preparation because the participant has not yet received the information regarding the next task to perform (see Meiran, Chorev, & Sapir, for supporting evidence). Nonetheless, extending the RCI resulted in a significant reduction in switching cost. We also manipulated task preparation time, the cue-target interval (CTI). CTI represents a period during which participants already know which task comes next and can prepare for that task. Accordingly, we found that increasingly the CTI strongly reduced switching cost. Finally, even when given plenty of time to prepare, participants seem to have been unable to eliminate switching cost. Based on these results, we decomposed switching cost into (1) *dissipation component*, related to cost that is reduced by increasing RCI; (2) *preparatory component*, reflecting cost reduced by increasing CTI; and (3) *residual component* (see Figure 1).

At a somewhat less technical level, mixing cost may be interpreted as reflecting performance decrement due to the mere relevance of several tasks rather than a single task. Switching cost represents performance decrement due to having just switched tasks. Its dissipating component

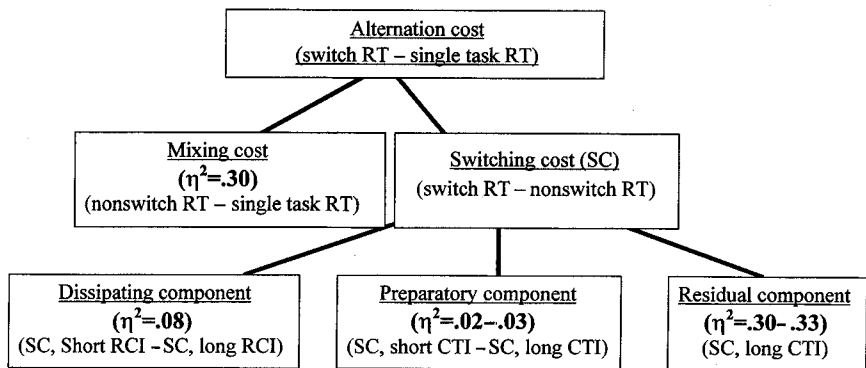


Figure 1. Components of alternation cost.* (η^2 values represent the proportion of aging-related variance in the specific component in Meiran, Gotler, & Perlman's, in press, experiments).

may be interpreted as set disengagement/forgetting and its preparatory component may be interpreted as resulting from set engagement.

Aside from these apparent differences, there is empirical evidence showing that the various components of alternation cost reflect different underlying processes or different combinations of underlying processes. The evidence is based on empirical dissociations, namely, variables that affect the components differentially (see Fagot, 1994, and Meiran, 2000b, for a partial list of these dissociations). The results concerning ageing constitute one of these dissociations, since old age is associated with a pattern of both relatively impaired and relatively intact components. In Figure 1, we present the proportion of old-age related variance (η^2) in each component of alternation cost in Meiran, Gotler, and Perlman's (in press) study. As may be seen, the proportion of old-age related variance was large for mixing cost (see also Hartley, Kieley, & Slabach, 1990; Kray & Lindenberger, 2000) and residual cost (especially De Jong, Emans, Eenshuistra, & Wagenmakers, 2000, but see also Salthouse, Fristoe, McGurthy, & Hambrick, 1998). In contrast, the effect of old age on preparatory cost was negligible (see De Jong et al., 2000; Hartley, et al., 1990; Kramer, Hahn, & Gopher, 1999; Kray & Lindenberger, 2000; and Mayr & Liebscher, this issue). There is an alternative explanation to this finding, suggesting that because the elderly are generally slower, this results in larger switching cost. If preparation was normal among the elderly, it should have resulted in larger reduction in switching cost than among young participants. The fact that preparatory cost was numerically similar in the two age groups suggests, according to this line of reasoning, that preparation was, in fact, less efficient among the elderly. The reason being that the proportional reduction in switching cost was smaller among the elderly, for whom the total switching cost was larger. However, we argue that the normal preparatory cost cannot be the result of general slowing, because the elderly exhibit switching costs in conditions in which young participants usually show zero residual costs (Meiran, Gotler, & Perlman, in press, Exp. 2). Put differently, general slowing may be interpreted as suggesting that all RTs are proportionally slowed. Accordingly, multiplying an effect with a size of zero by a proportional-slowing factor would result in zero, and we have found otherwise. To summarise, the performance of the elderly suffered relatively substantially from the mere presence of trials involving an alternative task (mixing cost), and from immediate switching (residual cost). However, the elderly were nearly as efficient as young participants in preparing for a task switch (preparatory cost).

Processing model

The second stage in our research involves identifying the processes that underlie the components (Meiran, 2000a, b). We suggest that the context

in which the tasks are intermixed makes some task elements multivalent. An example of a multivalent task element is a bivalent target stimulus such as *red-X* in a context where participants switch between colour discrimination and letter discrimination. It is bivalent because it is relevant for both tasks. Note that the same target stimulus would have been considered univalent if either colour or letter, but not both, were the only relevant dimensions.

To enable responding according to task requirements, task sets are activated whenever a given task element is multivalent. Each task set is responsible for one multivalent task element, (e.g., the target stimulus, the response, which arithmetic operation to perform, “-5” or “+3”, etc.). Moreover, task sets may be activated at different points in time. Some sets are activated by the instructional cues prior to task execution proper. This phenomenon, jointly termed “advanced reconfiguration”, is reflected in the reduction in switching cost by preparation (i.e., the preparatory component). Other task sets are activated later. One possibility is to activate the task set only after the presentation of a target stimulus, a phenomenon termed “stimulus cued completion [of reconfiguration]” (Rogers & Monsell, 1995). The other possibility, “retroactive adjustment” is to activate the task set after responding. This reflects learning from experience. Stimulus-cued completion and retroactive adjustment produce residual cost, which is cost that is unaffected by advanced preparation.

In the paradigm we used (Figure 2), participants were asked to perform two tasks involving position discrimination: RIGHT-LEFT, where the vertical dimension is to be ignored, and UP-DOWN, where the horizontal dimension is to be ignored. Thus, in this particular paradigm, the target stimuli as well as the responses were bivalent. Target positions were bivalent because one aspect of target position was relevant for the task at hand (and irrelevant for the alternative task) while another aspect was irrelevant for the task at hand but relevant for the alternative task. An example is the upper-left location, where the UP feature is relevant in the context of the UP-DOWN task but irrelevant in the context of the RIGHT-LEFT task. Similarly, LEFT is irrelevant in the context of the UP-DOWN task but relevant in the context of the RIGHT-LEFT task. Moreover, both of the physical responses (key presses) were used to indicate two nominal responses. For example, a given key press indicated both UP and LEFT, depending on the task. Therefore, the responses were also bivalent. Because the target stimuli as well as the responses were bivalent, two types of task set needed to be employed, a *stimulus task set* (S-Set), that deals with stimulus ambiguity, and *response task sets* (R-Sets), that deal with response ambiguity. The two types of set operate in a similar manner (although the sets themselves are adjusted differently). The S-Set and R-Sets act on low level representations in which relevant

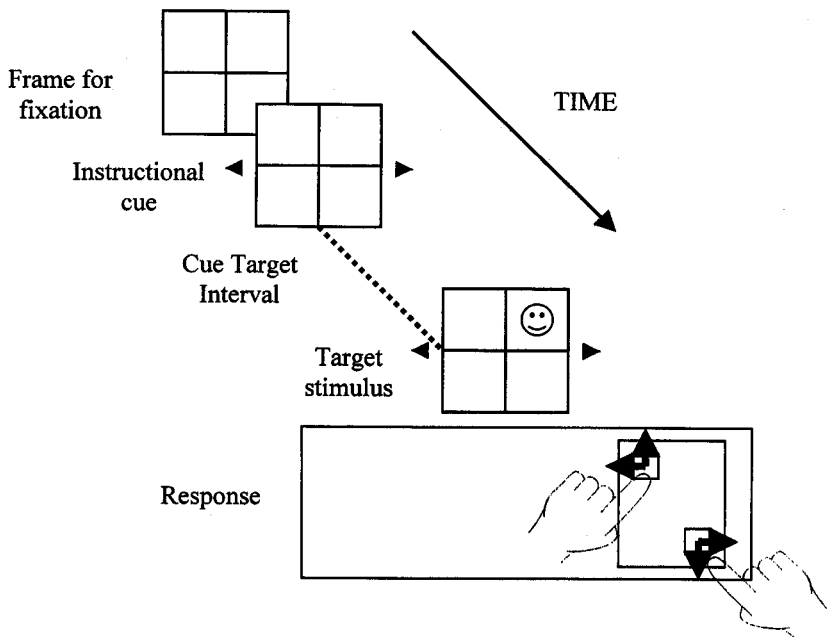


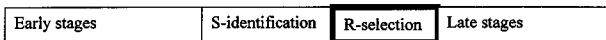
Figure 2. The experimental paradigm used by Meiran, Gotler, and Perlman (in press).

and irrelevant features are equally weighted. As a result of applying the task sets, more abstract representations are generated in which one feature is emphasised while the other feature is de-emphasised. For example, the application of the S-Set may result in representing a target stimulus positioned in the upper-left corner as mostly UP, with the feature LEFT being relatively de-emphasised or ignored. At present we cannot determine if emphasis is achieved by activating the relevant feature, inhibiting the irrelevant feature, or both. However, recent evidence suggests an important role of inhibitory influences (Mayr & Keele, 2000).

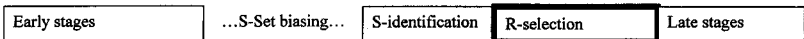
According to our model, switching costs arise in two separate processing stages (Figure 3). First, task-switching entails an added processing stage associated with advanced reconfiguration of the S-Set. Advanced reconfiguration involves the biasing of the S-Set such that features that correspond to the task-relevant dimension are strongly emphasised relative to irrelevant features. Second, because the R-Sets are adjusted after responding in Trial N-1, when a task-switch occurs in Trial N, these sets are inappropriately biased in favour of the wrong task. As will

Short CTI

No-Switch

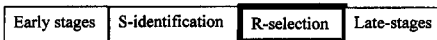


Switch



Long CTI

No-Switch



Switch



Figure 3. Processing stages affected by task switching (from Meiran, 2000a. Reproduced with kind permission of Springer-Verlag from Figures 2 and 3 in 'Modeling cognitive control in task-switching', *Psychological Research*, 63, 234–249).

become clearer soon, these inappropriate biases prolong response selection. Furthermore, since R-Set adjustment takes place after responding to Trial N–1, it is insensitive to the CTI in Trial N, which results in residual cost. In other words, we argue that residual cost is reflected in the prolongation of the response selection stage.

We have modelled response selection by a pattern-matching process, based on an interaction between abstract stimulus and response representations. The task sets act as filters, which block some parts of the information while emphasising other parts of that information (see Figure 4). Put differently, the S-Set is believed to reflect selective attention to a particular dimension in the target stimulus, while the R-Sets reflect selective attention to a particular dimension of the physical response. The dimensions of the physical responses (key presses) refer to the nominal responses which they indicate, e.g. "LEFT" for the RIGHT–LEFT task and "UP" for the UP–DOWN task.

An important difference between the S-Set and the R-Sets refers to the point in time in which these sets are being adjusted. The S-Set is adjusted prior to response selection, and this adjustment can take place during the CTI in response to the instructional cue. Therefore, the S-Set that is used in Trial N is adjusted according to the task-relevant dimension in Trial N.

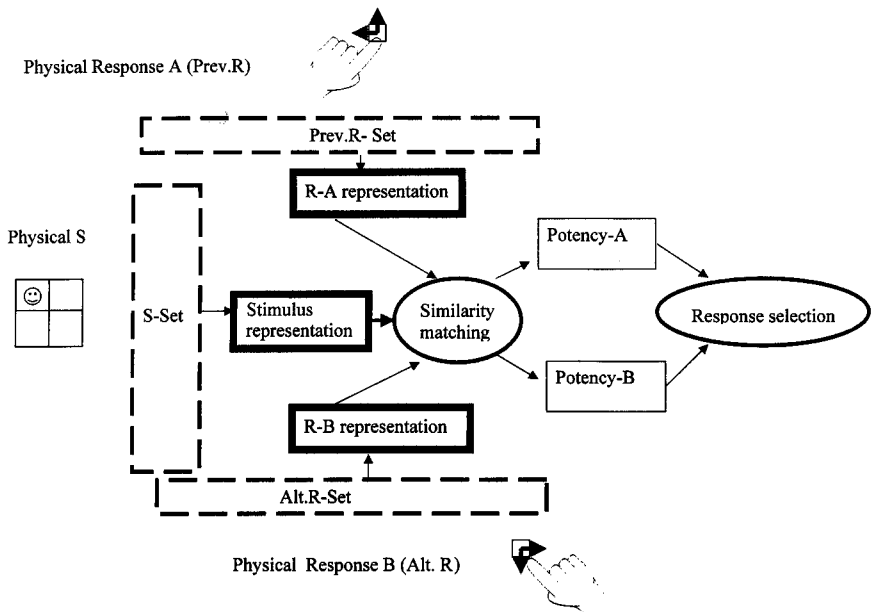


Figure 4. Outline of the processing model (from Meiran, 2000a. Reproduced with kind permission of Springer-Verlag from Figures 2 and 3 in 'Modeling cognitive control in task-switching', *Psychological Research*, 63, 234–249).

In contrast, R-Sets are adjusted, at least partly, by an incremental learning process taking place after responding. Therefore, the R-Sets used in Trial N were adjusted in Trial N–1, implying that the R-Sets are adjusted according to the task-relevant dimension in Trial N–1. In the case of a task repetition, the R-Sets are properly adjusted, because the task relevant dimension in Trial N happens to be the same as that in Trial N–1. However, in switch trials, the R-Sets are adjusted according to the wrong task. Given these features of response task sets, flexible intentional control over performance *in the given task-switching situation* is based primarily on control over the S-Set.

With respect to R-Set adjustment, we suggest that this process is based on labelling the physical responses (key presses) according to the nominal responses they indicate. For example, pressing a key to indicate the nominal response, "UP", presumably results in representing the key press as indicating UP more than LEFT. This learning process probably applies more strongly to the response that had just been emitted as

compared to the one which has not been emitted. Thus, the model includes a separate R-Set for each physical response.

Response selection in the model is based on determining the similarity between the abstract stimulus code and the abstract response codes. Consequently, each physical response gains *potency*, representing its "similarity" to the target stimulus, with the most potent response being selected. RT is determined by the relative potency of the responses, and thus reflects response competition. This description translates into a series of equations as explained later. Readers can skip the mathematical description and go directly to "Modeling task switching performance" but before they do so, we should explain the three most important parameters of the model. These include parameters representing the degree of bias (in proportions, with .50 representing no bias) in the task sets *during response selection*. Note that the task sets change their values dynamically, but these dynamics are *not* captured in the task-set parameters. The dynamics of S-Set adjustment are represented in another parameter, $W_{\text{CTL-S}}$, representing the duration, in ms, of the S-Set adjustment process preceding response selection (Figure 3).

W_S represents the S-Set bias in favour of the task-relevant stimulus dimension. If $W_S > .5$, this implies that the task-relevant stimulus dimension in Trial N is more heavily emphasised than the irrelevant dimension. $W_{\text{Prev.R}}$ and $W_{\text{Alt.R}}$ represent the bias of the R-Sets. This bias is in favour of the relevant dimension *in Trial N-1*. If $W_{\text{Prev.R}} > .5$ and/or $W_{\text{Alt.R}} > .5$, this implies that the task-relevant response dimension in Trial N-1 is more heavily emphasised than the irrelevant dimension in Trial N-1. An optimally biased S-Set would be associated with $W_S = 1$, reflecting perfect filtering of the irrelevant target-stimulus dimension. In task switching situations, an optimal value for both R-Sets would be .50, representing zero counter-productive post-response adjustment of the R-Sets. Adjusting R-Sets retroactively is productive in single-task conditions where the task in Trial N-1 is the same as the task in Trial N.

Two additional parameters are of interest. These parameters are related to the fact that the model does not yield true RT, but instead yields an analogue of RT*. The model is fit to experimental results by a search algorithm but changes the values of the parameters so that the Pearson correlation between RT and RT* is maximised. This correlation is related to a linear regression, whose two parameters, slope and intercept, are important in comparing age groups. Slope differences between groups reflect the relative speed of what may be broadly defined as response selection processes. The reason is that the slope parameter represents that variation in ms per one unit variation in RT*. Moreover, the variation in RT* is entirely due to the effect of response repetition, congruency, and task-switch, variables whose effects are being modelled. These variables

are believed to affect response selection—broadly defined, differences in the slope parameter represent the relative length of response selection. Along a similar line of argument, the (corrected) intercept represents the total duration of processes preceding or coming after response selection, namely stages that are unaffected by congruency task-switch, and response-repetition.

The mathematical description of the model

Formal description of stimuli and responses. Physical target-stimuli and physical responses are represented in the model as a quadruple of zeros and ones. The first two numbers describe the vertical dimension (UP and DOWN, respectively). The last two numbers describe the horizontal dimension (RIGHT, and LEFT, respectively). For example, the pattern "1,0,0,1", represents UP-LEFT. When the pattern refers to a target stimulus, it describes a location, such as the upper-left location. When it represents a physical response, it describes the nominal responses that are indicated by committing that physical response. For example, the previous list describes the physical Response A in Figure 4 because this physical response indicates two nominal responses, UP and LEFT.

Abstract mental codes of stimuli and the responses are quadruples of positive fractions, determined by multiplying the elements in the physical stimulus/response (1 or 0) by the appropriate weights. The weights serve as task-sets. S-Set is related to w_s ($0 \leq W_s \leq 1$), representing the bias in favour of the task-relevant dimension in the current trial (Trial N). Accordingly, $1-W_s$ is the weight assigned to the task-irrelevant dimension. How the S-Set is applied may be clearer when we consider the example where the task is UP-DOWN, making the relevant stimulus dimension the vertical dimension. In this case, W_s may equal .95, which implies that the (task-relevant) vertical dimension is much more heavily weighted than the horizontal dimension, that is, the irrelevant dimension receives a weight of $1-W_s = .05$. Continuing the example, the abstract representation of the upper-left target stimulus ("1,0,0,1") would be " $W_s, 0, 0, 1-W_s$ ", or ".95, 0, 0, .05".

Unlike the S-Set, where the weight represents the bias in favour of the task-relevant dimension in Trial N, *in the R-Sets, the weights represent the bias in favour of the dimension that was task-relevant in Trial N-1*. Accordingly, $W_{\text{Prev.R}}$ represents the bias in Prev.R, and $W_{\text{Alt.R}}$ represents the bias in Alt.R ($0 \leq W_{\text{Prev.R}}, W_{\text{Alt.R}} \leq 1$). The application of the R-Sets is strictly analogous to the application of the S-Set.

Response selection. Response selection has three separable aspects: Similarity matching, response decision, and RT modelling.

Similarity matching. This process determines which response is "most similar" to the target stimulus, so that a greater degree of similarity results in a relatively potent response. Equation (1) is used to calculate the potency of Response 1, where 1 stands for A (Response A) or B (Response B).

$$(1) P_1 = \sum_{i=1}^k S_i R_{li} \quad (1 = A, B)$$

(k being the number of elements in a list. In the present case $k = 4$).

Response decision and reaction time. Using response potencies, response strength (Str.) is computed as follows:

$$(2) \text{Str.} = P_A - P_B$$

Equation 2 serves two functions: Determining which response is selected, and calculating RT^* . The sign of Str. determines which response was more potent, and hence, selected, while $|\text{Str.}|$ is related to the quickness of the response, hence:

$$(3) RT^* = 1/|\text{Str.}|$$

With RT^* being an analogue of RT. Note that the response that was not selected still affects the value of Str. and consequently, affects RT^* . This fact reflects the role of response competition, so that a strong competing response results in slower RT.

Model fitting. Note that the equations do not relate the experimental conditions to RT, but to an analogue of it, RT^* . In order to fit the model to experimental results, it was assumed for simplicity's sake that RT^* is linearly related to RT. Thus, we used a search algorithm to change parameter values in order to maximise the Pearson correlation between RT^* and RT. Since the Pearson correlation reflects the strength of the linear between RT and RT^* , we also report the parameters in the linear regression relating RT to RT^* .

Modelling task switching performance

In this section, we fitted our model to results of Experiment 1 from Meiran, Gotler, and Perlman (in press). The experiment was run in a Kibbutz in the southern part of Israel. An advantage of testing this

population is that these people live in a relatively closed community and are relatively homogenous in educational and occupational background. Therefore, the samples of 16 elderly (ages 64–76, mean = 68.3) and 16 young participants (ages 20–29, mean = 24.1) were matched quite closely on these variables (4 additional elderly participants were excluded from the analysis because of making more than 50% errors in the incongruent condition). We used a health questionnaire to exclude participants with a past or present psychiatric diagnosis, and conditions that are likely to affect the brain functioning including hypertension, diabetes, tumours, head trauma, and so forth. The elderly participants were high functioning at the time of the test. There were no significant differences between the groups in vocabulary scores (means, out of 40 were 30.6 and 33.5 for the young and the elderly, respectively), years of education (12.4 and 12.9), or sex distribution (8/8 and 6/10 males/females). In the single-task condition, half of the participants performed the UP–DOWN task and half performed the RIGHT–LEFT task.

The experiment was run as a single session. Participants were first tested in the mixed tasks condition (20 warm-up trials followed by 4 identical blocks, 80 trials each) followed by the single-task condition (1 block of 80 trials). The reason for including the single-task condition at the end of the experiment was that we did not wish to change the relative difficulty of the two tasks when they were mixed. Each trial consisted of: (1) an empty grid presented for a constant RCI of 2032 ms; (2) the presentation of the instructional cue for a variable CTI (116 and 1016 ms); and (3) the presentation of the target stimulus until the response. 400 Hz beeps for 100 ms signalled errors. The instructional cues changed in the mixed-task condition, and were constant in the single-task condition. Participants were explicitly informed regarding the transition to a single task block.

Unlike Meiran, Gotler, and Perlman's (in press) study, we included response-repetition as an independent variable, which is necessary for modelling purposes. Specifically, response-repetition is the variable differentiating $W_{Prev.R}$ from $W_{Alt.R}$. Trials following an error or following a RT exceeding 5 s were excluded. RT in the remaining trials was not analysed if it exceeded 5 s or the response was erroneous. In order to save space we shall restrict the report to the effects involving the added independent variable, response repetition. Alpha was .05. In the analysis of the mixed-tasks condition we found the usual significant interaction between response-repetition and task-switch (e.g., Fagot, 1994; Meiran, 1996, 2000a; Rogers & Monsell, 1995), $F(1, 30) = 22.96$, $MSE = 26658$. Specifically, response-repetition speeded nonswitch RT but slowed switch RT. The triple interaction involving response-repetition, task-switch, and age was nonsignificant. This result indicates that the size of the two-way

interaction between response-repetition and task-switch was similar in the two age groups. In our model, the interaction between task-switch and response-repetition is explained by the difference in retroactive-adjustment between the executed response (reflected in the parameter $W_{\text{Prev.R}}$), and the response, which has not been executed ($W_{\text{Alt.R}}$). Thus, one would expect that the difference between these parameters would be similar in the two age groups, as we have found (see later). In other words, the young participants and the elderly tended to adjust the R-Set of the executed response more than the response that has not been executed.

In the analysis of single-task performance, we excluded the first eight trials in which RT was relatively long. There was a just significant interaction between CTI and response-repetition, $F(1, 30) = 4.14$, $MSe = 2213$, $p = .051$. It indicated that response repetition was facilitatory only when CTI was long (628 vs 610ms), whereas a weak trend in the opposite direction was found when CTI was short (654 vs 659ms), for non-repeated and repeated responses, respectively. Our model has little to say about this interaction.

Modelling results

Since the participants were elderly volunteers, we could not test them for very long periods, which resulted in a relatively small number of observations per condition. In order to increase the stability of the results, we modelled group means.

Mixed tasks. We modelled the results including 32 mean RTs. These reflected conditions formed by crossing task-switch, CTI (short/long), congruency (whether the same physical response is indicated as the correct response in the two tasks—*congruent*, or whether the two tasks indicate different correct physical response—*incongruent*), Block (1–2 vs 3–4), and response-repetition. Modelling was performed in each age group, separately (Table 1). The free parameters included the three parameters representing the task-sets (given in proportions), and four additional parameters (given in ms). The additional parameters were (a) W_{CTI} , representing the reduction in RT in the nonswitch condition due to increasing CTI, and (b) $W_{\text{CTI-S}}$, representing the additional reduction in RT in the switch condition. W_{CTI} represents general preparation processes, such as phasic alertness and the prediction of target onset (see Meiran, Chorev, & Sapir, 2000a). In contrast, $W_{\text{CTI-S}}$ represents the size of the preparatory component, which, according to our model, reflects the time it takes to bias the S-Set (Figure 3). (c) W_{Block} and (d) $W_{\text{Block-S}}$ representing the effect of Block (practice) in the nonswitch condition and the additional effect of Block in the switch condition, respectively. All of the four additional parameters represent differences between means, and as such, the

TABLE 1
Modelling results: Mixed tasks performance

	Young	Old	Proportional age-related decrement
W_S	.955	.934	.46**
$W_{Prev.R}$.539	.546	.17***
$W_{Alt.R}$.518	.534	.89***
$W_{Prev.R} - W_{Alt.R}$.021	.012	
W_{CTI} (ms)	105	181	
W_{CTI-S} (ms)	87	140	
W_{Block} (ms)	99	201	
$W_{Block-S}$ (ms)	47	97	
RT*-RT slope	465	922	.98
RT*-RT intercept	-200	-608	
Corrected intercept	265	314	.18
R^2	.960	.967	

Because the minimal RT = 1, the minimal predicted RT, or the corrected intercept, equals Slope + Intercept.

**Because perfect selectivity implies $W_S = 1$, the decrement was calculated in terms of the difference between the actual selectivity and perfect selectivity, which was .045 for the young participants and .066 for the elderly.

***Because the best strategy is an unbiased response set (.5), age-related decrement in performance was computed based on the difference between actual biasing and the perfect strategy.

respective effects could have been detected in an ANOVA. In this respect, the model contributes little to our understanding over more standard methods of analysis. The main contribution of the model is in estimation of the three task-set parameters (those represented in proportions).

Features common to both groups. The results indicated a reasonable degree of fit, with R^2 values .960 and .967. This suggests that, as far as we can tell, the model described the strategy of the participants reasonably well. Moreover, if this conclusion is valid, the results also indicate that the strategies adopted by the young and elderly subjects were similar. w_S values indicate that, *when response selection took place*, the task relevant stimulus dimension was strongly emphasised/attended relative to the irrelevant dimension. Note that, according to the model, W_S does not depend on CTI. The reason is that participants are assumed to take as long as needed to bias the S-Set before allowing for the next processing stages to take place (Figure 3). Thus, CTI presumably affects the time it takes to accomplish S-Set biasing (W_{CTI-S}) but CTI does not affect the degree of bias which has been achieved (W_S).

$W_{Prev.R}$ was always larger than $W_{Alt.R}$, a feature that explains the

reversal of the response repetition effect in the switch condition (Meiran, 2000a). In explaining this interaction we will use an example. Consider a sequence of trials where Trial N-1 involved the UP-DOWN task and the participant pressed the upper-left key to indicate UP. Consequently, the code for the upper-left response key was adjusted, giving more emphasis to UP (e.g., 6) than to LEFT (e.g., 4). Since the lower-right key was not pressed in Trial N-1, its code was either adjusted more moderately than that of the upper-left key (e.g., .55 and .45) or was not adjusted at all (.5 and .5).

After switching to the RIGHT-LEFT task in Trial N, repeated selection of the upper-left response key would be relatively difficult as compared to selecting the lower-right key press. This is because LEFT is more strongly de-emphasising in the response code corresponding to the upper-left key (.4 in the example) than RIGHT is in the code of the lower-right key (.45 or .5). This explains why response repetition in the context of task switching is associated with response slowing. If, however, Trial N involves task repetition, repeating the response would lead to facilitation, since the relevant interpretation is emphasised in the response. Using the previous example, repeated pressing of the upper-left key to indicate UP would be facilitatory, since UP is relatively strongly emphasised in the mental representation of the response.

Global group differences. An interesting question is to what degree do the differences in the task sets explain the effects of old age on task-switching performance. In an attempt to answer this question, we predicted RT while using the parameters obtained among the young participants, excluding the three task-set parameters. This combination of parameters, when put into the model, simulates the pattern of RTs of a participant who is like the typical young participant in every respect, except for having task-set parameters that are like those obtained by a typical old participant. As a result, we could compare the predicted RT from a typical young participant to that of the simulated participant. This analytic strategy allowed us to examine the changes in RT that are purely due to the change in task-set parameters. Changing the task-set parameters resulted in the following changes in the predicted RT: There was an increase of 28% in switching cost (from 92 to 117 ms), an increase of 27% in congruency effect (from 94 to 119 ms), and a small (4%) increase in mean RT (795 vs. 767). In other words, the fact that the elderly were slower in general is not explained by the differential parameter values, as would be expected, because changing the parameters resulted in only a tiny increase in mean RT. General slowing is explained by the RT-RT* regression parameters, as explained later. Given that, the differential parameter values may be taken as reflecting effects not due to general slowing. These

include the increased (residual) switching cost and congruency effects. Put differently, when general slowing is accounted for by the remaining parameters, a change in the task-set parameters alone resulted in a considerable increase in switching cost and in congruency effects.

Focal group differences. Another way to examine the results is to look at the proportional change in each parameter due to old age. Two parameters were strongly affected by old age. The deviation of $W_{Alt.R}$ from .5 was almost doubled, reflecting the fact that, among the elderly, the difference between the two R-Sets was rather small. This finding indicates that older participants adjusted both response sets retroactively, not only the one associated with the response in Trial N-1. The adjustment of both R-Sets is another expression of the nonsignificant triple interaction between age, response-repetition, and task-switch (see earlier). With respect to the difference between the two R-Sets, Meiran (2000a, b) suggested that the retroactive adjustment of the R-Sets is partly due to response coding (Hommel, 1997), whereas the cognitive representation of the response is linked to its outcome. In the present case, the outcome of a key press was the expression of a nominal response (e.g., "UP"). Because this process applies only or mostly to the response which has just been emitted and not to the alternative response, it is reflected in the difference between $W_{Prev.R}$ and $W_{Alt.R}$. Given the fact that the difference was similar in the two age groups, one may conclude that response coding is not strongly affected by old age.

If response coding does not differentiate between the age groups, then what explains the enlarged residual switching costs among the elderly? In order to answer this question we need to return to the characteristics of the model. In the model, residual cost results from an interaction of two factors. The most important factor is the retroactive adjustment of the R-Sets. However, this factor interacts with the degree of bias in the S-Set. Note that the S-Set is not influenced by the preceding trial, and thus, by itself could not generate switch cost. However, lesser emphasis given to the relevant target-stimulus dimension implies greater emphasis given to the *irrelevant* dimension. More attention to the irrelevant dimension accentuates the effects due to the fact that the irrelevant dimension is emphasised in the R-Sets after a task switch.

Returning to the question regarding residual switching costs in the elderly, the critical factor seems to be the fact that both R-Sets are adjusted retroactively and not only the R-Set of the executed response. One possibility is that, for some reason, the elderly tend to treat the two responses as a group, or an S-R mapping (see Duncan, 1977; Shaffer, 1965).

There were two parameters in the $RT-RT^*$ regression: slope and inter-

cept. Before explaining group differences we need to clarify an important point. Given the fact that minimal RT^* was 1, the minimal predicted RT equals intercept + slope, which is what we computed as the corrected intercept. The corrected intercept reflects the duration of processing stages that are not modelled (thus not affecting RT^*). Returning to the results, we found interesting between-group differences in the $RT-RT^*$ slope. The $RT-RT^*$ slope was nearly doubled among the elderly, while the (corrected) $RT-RT^*$ intercept increased by only 18%. Thus, the regression parameters indicate that old-age related slowing is not general. Old age has a strong influence on the duration of processes related to task switching, response repetition, congruency, and CTI, which we modelled and may be broadly labelled "response selection/preliminary response preparation". In contrast, the $RT-RT^*$ intercept represents the duration of low-level perceptual analysis and relatively advanced response preparation processes but were only mildly affected by old age. Such a pattern accords with the neuropsychological evidence, showing greater old-age related damage to the prefrontal cortex than to other brain regions (e.g., West, 1996).

Single task. Because only eight means were modelled (formed by crossing CTI, congruency, and response-repetition), the analysis should be regarded as tentative. In the present analysis, we forced the intercept and slope parameters to equal the values in Table 1 (which is why $RT-RT^*$ regression parameters are not included in Table 2). With these values we could predict RT and compare the predicted RT to actual RT. Thus, instead of maximising the Pearson correlation between RT and RT^* , we minimised the sum of squared differences between the actual RT and the predicted RT. The results are presented in Table 2 and indicate a poorer degree of fit among the elderly participants as compared to the young ones. While w_S dropped slightly compared to mixed task performance (which should result in a slightly poorer performance), the parameters representing the R-Sets increased appreciably, and more so among the elderly than among the young participants. The somewhat less strongly biased S-Set makes sense since a strongly biased S-Set is required in mixed task performance to ensure correct responding which, in turn, is dependent upon a strongly biased S-Set relative to the R-Sets (see Meiran, 2000a, for an elaboration of this point). In single-task conditions, where the R-Sets are correctly biased (because the task in Trial N-1 is the same as the task in Trial N), such a strongly biased S-Set is no longer required. Note that strongly biased R-Sets represent a reasonable strategy in a single-task condition. Presumably, a strongly biased R-Set reflects the strong (and accumulated) effects of R-Set adjustment, which makes sense given the fact that the physical responses would be consistently mapped

TABLE 2
Modelling results: Single task performance

	<i>Young</i>	<i>Old*</i>	<i>Proportional age-related decrement</i>
W_S	.944	.924	.36**
$W_{Prev.R}$.686	.753	.36***
$W_{Alt.R}$.686	.753	.36***
$W_{CTI}(ms)$	36	39	
R^2	.895	.964	

*The fitting process did not result in successful convergence in this case.

**Because perfect selectivity implies $w_S = 1$, the decrement was calculated in terms of the difference between the actual selectivity and perfect selectivity.

***The proportions represent an advantage of the elderly over the young participants. The estimates were computed by subtracting .50 (unbiased) from the estimates, thus representing the (productive) bias, which was .253 for the elderly and .186 for the young participants.

to their meanings. Learning response meaning makes little sense in mixed-tasks conditions where response meaning changes from trial to trial. For example, a given key press may indicate LEFT in Trial N-1 but it would indicate UP in Trial N. Interestingly, the elderly exhibited an advantage over young participants in their gain from single-task conditions.

The present analysis suggests R-Set adjustment as a common mechanism underlying the enlarged residual costs and mixing costs in old age. Specifically, the elderly exhibited stronger retroactive adjustment of R-Sets in single task conditions, where such adjustment is adaptive, but also in mixed-tasks performance, where such adjustment is counterproductive. The fact that the two R-Set parameters were equal suggests that the incremental retroactive adjustment process reached asymptote, so that the very last update (reflected in $W_{Prev.R}$) did not make a difference compared to less recent updates (represented by $W_{Alt.R}$). As in the analysis of mixed-task performance, we estimated the global effects of the task-set parameters by simulating the performance of a typical young participant. We compared the simulated performance to that of a simulated participant who was similar in every respect except for the task-set parameters, which were like those of a typical old participant. This time, the parameter replacement did not increase congruency effects. Actually, the predicted congruency effect *dropped* from 39 to 36 ms. This result is another expression of the fact that, while there were large old-age influences on congruency effects in mixed tasks conditions (the proportion of old-age related variance was $\eta^2 = .18$), these effects were

much smaller ($\eta^2 = .07$) and nonsignificant in the single-task condition. According to our model, congruency effects result from less than perfectly and correctly biased S-Set and R-Set. Given the stronger bias of the R-Sets in the single task condition, a bias which is even greater among the elderly than among the younger participants, congruency effects and age differences in these effects should become smaller, as we have found.

DISCUSSION

The present study represents an attempt to characterise task-switching performance in old age in terms of our model. The model has two aspects: describing which components are affected by old age, and estimating model parameters. The results from our laboratory (summarised in Figure 1), agree with most of the literature (Meiran, Gotler, & Perlman, in press, for a review) and indicate a substantial influence of old age on mixing cost and on residual cost (with age group accounting for roughly 30% of the variance in these components). Old age has a smaller influence on congruency effects (roughly 18%) and the rate of set dissipation (roughly 8%). However, old age has a negligible influence on preparatory cost (2–3%).

At the functional level, the modelling results point to four loci of old-age effects, including: (1) the intercept parameter in the regression of RT on RT*, (2) slope parameters in the same regression equation, (3) the task-set parameters, and (4) the duration of S-Set biasing. We will deal with each of them in turn.

The smallest influence of old age was found in the intercept parameter, representing processes preceding response selection and S-Set biasing and processes following response selection. These include low-level perceptual analysis, and relatively advanced response preparation processes. The largest influence of old age was on the slope parameter, suggesting that old age is associated with general slowing in processes related to response selection and initiation. This conclusion concurs with results in the literature showing that ageing has an especially pronounced effect on these processing stages (e.g., Allen, Madden, & Weber, & Groth, 1993; Allen, Smith, Vires-Collins, & Sperry, 1998; Hartley & Little, 1999). In this respect, the present results constitute an important converging operation.

With respect to task-set parameters, the most noteworthy influence of old age was on the R-Sets, illustrating the fact that the elderly had an increased tendency to adjust their performance based on their experience in the preceding trial. This result is completely novel and emphasises the potential of using an explicit modelling approach. For some reason, it appears that the elderly have treated the two responses as a group or

mapping. Regardless of this peculiarity, their tendency to learn from the preceding trial caused an advantage in the single-task conditions, but created a disadvantage in the mixed-task conditions. According to the present analysis, the reason why young participants were faster in single-task conditions was mainly due to their generally faster response selection processes, which (over)compensated for their lesser R-Set learning.

Counterproductive effects from the preceding trial, such as those found in the mixed-task conditions, are conceptually analogous to "internal noise", a term used to explain old-age effects in cognitive functioning (e.g., Allen, Weber, & May, 1993; Krueger & Allen, 1987). Thus, our results suggest that (a specific form of) cognitive noise may be an important factor in age-related deterioration in cognitive functioning. Unlike the R-Sets, old-age effects on the S-Set and on W_{CTI-S} were relatively modest. These parameters reflect selective efficiency, and the time it takes to adjust the attentional focus, respectively. Thus, our results support the hypothesis concerning selective attention deficits in old age (e.g., Hasher, Stoltzfus, Zacks, & Rypma, 1991). However, in the present case, the effect of ageing on internal noise (represented by the R-Sets) was much more pronounced than its effect upon attentional selection (the S-Set and W_{CTI-S}). This comparison, made possible by modelling, is yet another advantage of this approach.

To conclude, we used a modelling approach to clarify the reasons underlying age-related differences in task-switching performance. This approach has proven insightful and resulted in a rich and detailed description of performance. Our results led us to conclude that old age had a pronounced effect on the duration of response selection and resulted in an increased tendency to learn from the immediate past experience in the preceding trial. In contrast, old age was associated with relatively minor deficits in selective attention to the task-relevant stimulus dimension and processes preceding or following response selection. These characteristics were true for switching situations and single-task performance alike. The model we applied is still in its infancy, and future research should extend it, making it possible to explore a wide variety of switching paradigms. This is essential in order to examine the generality of the conclusions, as well as for testing their implications.

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