The Effect of Aging on Response Congruency in Task Switching: A Meta-Analysis

James A. Grange, PhD

School of Psychology, Keele University, UK

Raymond B. Becker

Faculty of Linguistics and Literary Studies, Bielefeld University, Germany

Word Count: 4,590

In Press—The Journals of Gerontology, Series B:

Psychological Sciences and Social Sciences

Author Note

We are grateful to Teal Eich, Nicole Anderson, and an anonymous reviewer for helpful comments on a previous version of this manuscript. The first author is grateful to Nick Garnett for discussion regarding linear mixed effects modelling. All raw data and analysis code are available to download from https://osf.io/3u9s2/. Please address correspondence to James A. Grange, PhD, School of Psychology, Dorothy Hodgkin Building, Keele University, Keele, UK, ST5 5BG. Email: grange.jim@gmail.com.

Abstract

Objectives: Response congruency effects in task switching are the observed slowing of response times for incongruent targets which afford more than one response (depending on task) in comparison to congruent stimuli that afford just one response regardless of the task. These effects are thought to reflect increased ambiguity during response selection for incongruent stimuli.

Methods: The present study presents a meta-analysis of 27 conditions (from 16 separate studies) whose designs allowed investigation of age-related differences in response-congruency effects on response time.

Results: Multilevel modelling of Brinley plots and state–trace plots showed no age-related effect on response congruency beyond that which can be explained by general age-related slowing.

Discussion: The results add to the growing body of evidence of no age-related decline in measures of attention and executive functioning.

Keywords: Task switching; congruency effects; response selection; aging; meta-analysis

The Effect of Aging on Response Congruency in Task Switching: A Meta-Analysis

Humans live in an incredibly rich, multi-task environment, with many stimuli competing for our attention. In order to act in a goal-directed manner, it is essential that the cognitive system is able to select the most relevant stimulus to act upon. But stimulus selection is only half of the battle, as many stimuli are multivalent; that is, there are often multiple tasks that can be performed on the same stimulus. For example, there are many tasks that can be performed on a computer, so it is essential that the cognitive system is able to select the correct task (e.g., check e-mails) in the face of competing alternatives (e.g., check the news). Once selected, this task must be represented in a stable manner in the system so that task-irrelevant intrusions do not occur. At the same time, this task representation must flexible enough so that when our goals change we can switch to a new one. The tension between stability on the one hand, and flexibility on the other, has been termed the *stability–flexibility dilemma* (Goschke, 2000).

This stability–flexibility dilemma can be investigated using the task switching paradigm, wherein participants are required to rapidly switch between simple cognitive operations on multivalent stimuli (see Grange & Houghton, 2014; Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010, for reviews). For example, participants might be presented with numerical stimuli (any digit from the set 1–9, excluding 5) and be asked to either make a parity judgement (i.e., odd/even) or a magnitude judgement (i.e., lower/higher than 5). The primary finding of interest in this literature has been the "switch cost": Response times (RTs) and error rates are increased on trials where the task switches from that of the previous trial (e.g., Parity—*Magnitude*) compared to task repetitions (e.g., Magnitude—*Magnitude*), and has been proposed as an index of cognitive control (but see Logan, 2003).

Due to this, the task switching paradigm has been a popular tool to study potential age-related decline in cognitive control (Kray & Ferdinand, 2014). In a recent meta-analysis, Wasylyshyn, Verhaeghen, and Sliwinski (2011) found—after taking into account the general slowing typically found in older adults—no age-related decline for RT switch costs, suggesting no age-related decline in cognitive control. Wasylyshyn et al. (2011) did find clear age-related decline in the ability to sustain focus on a single task in multi-task situations, as indexed by the "mixing cost": Slower RTs to task repetitions in blocks where switches are possible (i.e., mixed-blocks) compared to task repetitions within pure-blocks, where only one task is required; this cost is thought to be associated with the costs of maintaining a task representation within a switching context (see Marí-Beffa & Kirkham, 2014, for a recent review).

Much of the task switching literature has focussed on the switch cost as a measure of cognitive control. Mirroring this focus, much of the task switching and aging literature—including the meta-analysis of Wasylyshyn et al. (2011)—has focussed on the switch cost together with the mixing cost. However, the switch cost is just one among a constellation of task switching phenomena that potentially reflect cognitive control processes; a complete model of cognitive control during task switching must go beyond explaining the switch cost and outline functional mechanisms that give rise to the whole constellation of effects observed (see Altmann & Gray, 2008, for one such attempt).

The purpose of the present paper is to examine potential age-related decline in the *response congruency effect* in task switching. In the task switching paradigm, stimulus–response mappings are typically overlapping: In the example outlined above, the responses "Odd" and "Lower than 5" might be mapped to a left response key, and the responses "Even" and "Higher than 5" might be mapped to a right response key. Congruent stimuli require the same response regardless of the task (e.g., a stimulus "1" is both odd and lower than 5, and as such always requires a left response); incongruent stimuli require different responses depending on the task (e.g, a stimulus “7” is odd and higher than 5, so the correct response depends on what the task currently is). Thus, for incongruent stimuli, there exists ambiguity during response selection which must be overcome by the cognitive system to arrive at a correct response (e.g., Schneider, 2015b). It is a well-replicated finding that response times and error rates are increased for incongruent stimuli compared to congruent stimuli. The magnitude of this response congruency effect can be thought of as the degree to which stimulus ambiguity interfered with response selection.

Given that the response congruency effect provides important insight into the mechanisms of response selection during task switching (Schneider, 2015a; 2015b; Schneider & Logan, 2015), it is perhaps surprising that this has not been the focus of much empirical work within cognitive aging research. Such a deficit might be expected, as a prominent hypothesis of cognitive decline in healthy ageing is the inhibition-deficit hypothesis of Hasher and colleagues (Hasher, Lustig, & Zacks, 2007; Hasher, Zacks, & May, 1999), which proposes that cognitive inhibition—and hence the ability to effectively deal with interference during response selection—becomes less efficient with age.

As already stated, many aging and task switching studies have not focussed on the response congruency effect, yet many of these studies’ empirical designs afforded such analysis. Of the studies we reviewed, only three were directly designed to assess age-related differences in response congruency effects. Meiran et al. (2001) found larger response congruency effects for older adults compared to younger adults on task switch trials compared to task repetition trials. Similar findings were also found by Eich, Rakitin, and Stern (2016b) with incongruency increasing error rates more for older adults than younger adults in mixed-blocks compared to pure-blocks. Eich et al. (2016a) examined 75 older adults and 62 younger adults in a task switching paradigm together with functional magnetic resonance imaging (fMRI) to examine age-related effects on response congruency effects in pure-blocks and mixed-blocks. Whilst the response time analysis found no interaction between age and congruency, the accuracy data showed larger response congruency effects for older adults in the mixed-blocks compared to the pure-blocks. The fMRI data revealed that "...older adults recruited an additional set of brain areas in the ventral attention network to a greater extent than did younger adults to resolve congruency-related response-conflict" (Eich et al., 2016a, p.211).

The Current Study

The purpose of the present study was to assess whether the response congruency effect is influenced by healthy aging by conducting a meta-analysis. As stated, although many aging and task switching papers have not focussed on the response congruency effect, many of their empirical designs afforded such an analysis. Therefore, this meta-analysis provides an important—hitherto rather neglected—assessment of response congruency effects in task switching during healthy aging.

Method

Study Selection

Studies were selected after a search using the EBSCO electronic database, which—among others—searches PsycINFO and MEDLINE databases using the search terms "(task switch* OR set switch*) AND (ageing OR aging)", together with the ancestry approach. The literature search ended on 10th April, 2017. A study was only included in the analysis if: (a) the response requirements were overlapping (allowing for congruency); (b) the paradigm presented was typical of standard task switching designs (for example, the "fade-out" condition of Spieler, Mayr, and LaGrone (2006) was not included); (c) only two tasks were presented to participants (defining congruency is more complex with three or more tasks; but see Schneider, 2014).

The above criteria left 40 studies for potential inclusion; these studies (and the respective quasi-experiments and/or conditions within these studies) are presented in the Supplementary Material (Appendix A). Data were extracted from tables presented within the studies, from graphical presentation of response times using the `g3data` graph visualiser (Frantz, n.d.), or by contacting the corresponding author if the data were not presented in the paper. The data missing from Appendix A were a consequence of either no response from the corresponding author after two separate requests for data, or the data being no longer available. The above exclusions and data limitations left 16 studies and a total of 27 data points for inclusion in the analysis.

Analytical Approach

For this study we focussed on response time (RT) as the dependent variable. RT is the typical dependent variable in task switching research, but we also chose to focus on RT as data for this were more readily available in the studies selected. Data were only collected from mixed-blocks, where both possible tasks are relevant. The data were collapsed across task repetition and task switch trials, again as this was more readily available in the studies selected (we return to the validity of this choice in the General Discussion).

The “dull” hypothesis (Perfect & Maylor, 2000) is to expect numerically larger congruency effects for older adults compared to younger adults, but note that such a finding does not allow the conclusion that there are age-related deficits specific to overcoming ambiguity in response selection because merely comparing overall RT does not take into consideration the ubiquitous age-related slowing (Verhaeghen, 2014). We followed the example of Wasylyshyn et al. (2011) by constructing and analysing Brinley plots, which plot—for each quasi-experiment and/or condition within each study in the meta-analysis—the mean RT for older adults against the mean RT for younger adults for congruent and incongruent trials. If—statistically—one regression line sufficiently explains the relationship between older and younger adult RT for all data points (which include congruent and incongruent performance) then one can assume that performance differs only along a single dimension of age-related slowing. If, however, separate regression lines are required (one for congruent and one for incongruent conditions) this would provide evidence of specific age-related impairment in response selection over and above that explained by age-related slowing (Verhaeghen, 2014).

In our analysis, we thus regressed the mean RT of older adults onto the mean RT of younger adults using linear mixed effects modelling, which takes into account the nested structure of our data (some studies had multiple quasi-experiments and/or conditions). We tested whether one regression line was sufficient to describe the relationship, or whether separate regression lines for congruent and incongruent trials were required. We complemented our Brinley-plot analysis with state–trace analysis, which regressed mean RT for incongruent trials on mean RT for congruent trials separately for older and younger adults across all of the studies. Similar to Brinley plots, if one regression line explains the relationship, then it can be concluded that incongruency impairs older adult performance in a similar way to younger adults. However, if separate lines are required (one for older adults, one for younger adults), this suggests specific age-related impairment in response selection.

Verhaeghen (2014) recommends complementing Brinley plots with state–trace analysis because "...state traces involve within-study comparisons, and Brinley functions involve both within-study and between-study comparisons." As such, "...state traces then reduce the amount of variance due to sampling or individual differences" (Verhaeghen, 2014, pp.36).

The second advantage pertains to interpreting any age-related effect found in the Brinley analysis (i.e., separate regression lines), which on its own is not diagnostic as to the nature of the effect incongruency might be having on older adult performance. If separate lines are required, finding parallel lines (i.e., identical regression slopes) for older and younger adults suggests the age-related impairment is due to the insertion of an addition process during response selection in older adults; finding non-parallel lines (i.e., an interactive effect) suggests that aging impairs each stage of response selection, but no additional processes are introduced Verhaeghen (see 2014, for a mathematical overview of this rationale). The state–trace analysis was also analysed using linear mixed effects modelling.

Results

The raw data are in Appendix A. For younger adults, there was a 99ms response congruency effect ($M_{incongruent}$ = 887ms; $M_{congruent}$ = 788ms). For older adults, there was a numerically larger response congruency effect of 150ms ($M_{incongruent}$ = 1367ms; $M_{congruent}$ = 1217ms).

All analysis was conducted using `R` statistics (R Core Team, 2015). We modelled the data using linear mixed effects modeling with the R package `lme4` (Bates, Mächler, Bolker, & Walker, 2015). We modeled the data using random intercepts[1] for each condition[2] nested within each study[3]. All models were fit using maximum likelihood.

[1] We attempted to model the data using random slopes for the effect of congruency within each study but experienced convergence issues during the model fit (likely due to the small number of data points from each study). Ignoring the warning messages regarding poor convergence produced model fits that were qualitatively similar to that reported in the text.

[2] We use the term "condition" for simplicity to refer to studies with a single quasi-experiment and multiple conditions (e.g., manipulating preparation intervals), but we also use this term to refer to studies with multiple quasi-experiments (i.e., separated in the paper as "Experiment 1", "Experiment 2" etc.). Table A1 in the Supplementary Material (Appendix A) includes information as to which "conditions" were extracted from each study.

[3] We also fit the data using models where study and condition were not nested (i.e., separate random intercepts for condition and study) to rule out shrinkage due to the nested design. The results were qualitatively the same as reported in the main body.

For both the Brinley and the state–trace analysis we log-transformed the data to achieve normally-distributed residuals of model fit, as assessed via visual inspection. Whilst linear mixed models are generally robust to violations of this assumption, the fit routine for the state–trace analysis in lme4 produced warnings regarding the scale of data. Transformation did not change the outcome of the analysis.

Brinley Plot Analysis

The non-transformed data are shown in Figure 1A. Visual inspection of this plot suggests that all data (incongruent and congruent) fall along a single dimension, suggesting a single regression line would be sufficient to explain the data.

We assessed the sufficiency of the number of regression lines required in the Brinley analysis using two approaches. In the first, we fit four different models to the data, and compared their AIC and BIC statistics. AIC and BIC are assessments of model fit whilst penalising models for their complexity. Models with the lowest AIC and BIC statistics are to be preferred. In the second stage we used likelihood-ratio tests to statistically compare the goodness of fit of the best model to all other models.

The four models were as follows:

1. Older adult RT predicted from just random effects (i.e., a 'null' model).
2. Older adult RT predicted from younger adult RT and random effects (i.e., a single-regression line).
3. Older adult RT predicted from younger adult RT, a main effect of "congruency", and random effects (i.e., a main effect model).
4. Older adult RT predicted from younger adult RT, a main effect of "congruency", an interaction of RT-younger and congruency, and random effects (i.e., an interaction model).

Congruency was centered in the analysis. Centering younger adult RT produced numerically-identical fit statistics, so we left it un-centered to aid visual interpretation of the model. The model specifications and fit statistics are shown in Table 1; the log-transformed data together with the fit of the best model is shown in Figure 1B. The AIC and BIC criteria both select the single regression line model (Model 2) as the best fitting model. This was confirmed using likelihood-ratio tests. The model with RT-older being predicted from RT-younger (Model 2) had a better goodness of fit compared to a model with just the random effects model (Model 1), $\chi(1) = 89.05$, $p < .001$. Adding a main effect of congruency (Model 3) did not improve the goodness of fit, $\chi(1) = 0.18$, $p = .67$, nor did adding a main effect of congruency and its interaction with RT–younger (Model 4), $\chi(2) = 1.54$, $p = .46$. The best-fitting model (Model 2) had an intercept of 1.242 (SE = 0.314), and RT-younger coefficient of b = 0.878 (SE = 0.046)[4].

State–Trace Analysis

The non-transformed data for the state–trace analysis is shown in Figure 2A. Visual inspection of the plot suggests that all data (older- and younger-adults) fall along a single dimension, suggesting a single regression line would be sufficient to explain the data.

Model assessment used the same two-stage approach as for the Brinley analysis. Again, we modelled the data using random intercepts for each condition nested within each study[5]. The four models were as follows:

---

[4] It is usual for the slope of the regression line in Brinley plots to be greater than unity (Verhaeghen, 2014). Note, though, that the finding of a slope less than one in this study is due to the log-transformation of response times. With untransformed data, the slope of the regression line is larger than unity (intercept = 63.56 [SE = 117.77]; b = 1.47 [SE = 0.11]).

[5] We again attempted to model the data using random slopes for the effect of age within each study but experienced convergence issues during the model fit. Ignoring the warning messages regarding poor convergence produced model fits that were qualitatively similar to that reported in the text. We also fit the data using models where study and condition were not nested (i.e., separate random intercepts for condition and

1. Incongruent RT predicted from just random effects (i.e., a 'null' model).
2. Incongruent RT predicted from congruent RT and random effects (i.e., a single-regression line).
3. Incongruent RT predicted from congruent RT, a main effect of "age", and random effects (i.e., a main effect model).
4. Incongruent RT predicted from congruent RT, a main effect of "age", an interaction of RT-congruent and age, and random effects (i.e., an interaction model).

Age was centered in the analysis. Centering congruent RT produced numerically-identical fit statistics, so we left it un-centered to aid visual interpretation of the model. The model specifications and fit statistics are shown in Table 2; the fit of the best model is shown in Figure 2B. Whilst the BIC statistic clearly prefers a single regression line model (Model 2), the AIC statistic appears to prefer an interaction model. However, closer inspection of the AIC values shows little difference between the full interaction model (Model 4, AIC = -127.76) and the single regression line model (Model 2, AIC = -127.49). Visual inspection of the two models' fit to the data (Supplementary Material, Appendix B) shows little effect of the interaction, and as such we prefer the simpler model of a single regression line.

This selection was confirmed using likelihood-ratio tests. The model with RT-incongruent predicted from RT-congruent (Model 2) had a better goodness of fit compared to a model with just the random effects model (Model 1), $\chi(1) = 170.43$, $p < .001$. Adding a main effect of age (Model 3) did not improve the fit, $\chi(1) = 0.13$, $p = .72$, nor did adding a main effect of RT-congruent together with its interaction with age (Model 4), $\chi(2) = 4.27$, p

study) to rule out shrinkage due to the nested design. The results were qualitatively the same as reported in the main body.

= .12. The best-fitting model (Model 2) had an intercept = 0.327 (SE = 0.138), and RT-congruent coefficient b = 0.966 (SE = 0.020)[6].

General Discussion

The present study utilised a meta-analytical approach to establish whether there is evidence for age-related differences in response congruency effects in task switching, an effect that reflects ambiguity during response selection involving recently-learned stimulus–response mappings. The result of both the Brinley analysis and the state–trace analysis provides no clear evidence for age-related effects on response congruency beyond that which can be explained by general slowing in older adults. In both analyses, a model with a single-regression line was sufficient to explain the data.

These results are important because the response-congruency effect has been somewhat neglected in research investigating age-related effects in task switching designs. Despite many published aging and task switching studies having designs capable of measuring response congruency effects, only three studies have directly addressed this question. Meiran et al. (2001) found larger response congruency effects for older adults compared to younger adults on task switch trials compared to task repetition trials, a pattern which was also found by Eich et al. (2016b) and Eich et al. (2016a) in accuracy data. It is not immediately clear why the three studies that have examined congruency effects explicitly do find age-related effects in contrast to the current results. There were no clear divergences between the design of the studies that directly assessed response congruency and other studies included in the meta-analysis (Supplementary Material, Appendix A). In addition, the mean age of the participants in each study, and the degree of practice experienced by

[6] Note that, as with the Brinley-analysis, the finding of a slope less than one in this study is due to the log-transformation of response times. With untransformed data, the slope of the regression line is larger than unity (intercept = 6.93 [SE = 47.09]; b = 1.09 [SE = 0.04]).

participants in each study (operationalised as the number of trials in the design) did not moderate the effects reported here (see Supplementary Material, Appendix C).

Below we outline some limitations which should be considered when drawing conclusions from our study.

Limitations

Although—to the best of our knowledge—our meta-analysis included all available data on response congruency effects in task switching, the final sample size is rather small, and thus has reduced power capable of detecting a true effect of aging on response congruency effects. This might be important for the state–trace analysis where a hint of an interaction was present (but see Supplementary Material, Appendix B). In addition, of the studies included in the analysis, only three explicitly addressed—and hence were designed with the intention of measuring—response congruency effects. So, power in the individual studies may also be reduced due to the design not being optimised for analysing congruency effects.

Another limitation is that we only entered response time data into our meta-analysis. This was a practical decision because response time data were more readily available in published work, and data were difficult to obtain when the relevant information was not included in the publication. This could be an important limitation because finding no age difference in the congruency effect in response time says nothing about whether there are age effects in accuracy, as we cannot establish whether accuracy was equated between age groups in the studies. In relation to this, of the three studies that have examined age-related effects of response congruency, two found no effects in the response time data but an age-related difference in the accuracy data. Thus, whilst our analysis suggests no age-related effect on response-congruency in response time data, it remains unclear whether a true effect of aging exists in accuracy data. More work will be required to ascertain this.

Another possible limitation is that we—again due to practical reasons—collapsed our data across task sequence manipulations (i.e., task repetitions and task switches). Note though that all data were taken from mixed blocks, and not from pure blocks. This decision may not be of consequence, because current evidence suggests that response congruency effects do not consistently interact with task sequence manipulations (Meiran, 1996; Meiran, Chorev, & Sapir, 2000; Monsell, Sumner, & Waters, 2003; Schneider, 2015b).

Another potential limitation lies in the fact that it cannot be ascertained how response selection was achieved in the current studies. Schneider and colleagues (Schneider, 2014, 2015a, 2015b; Schneider & Logan, 2015) have outlined two routes for response selection in task switching which produce response congruency effects. In the *mediated* route, response selection requires forming a representation of the response categories afforded by the stimulus (e.g., the stimulus "1" affords the response categories ODD and LOWER); response selection then proceeds according to the category–response rules in the study (e.g., ODD requires a left response). This route is mediated because the category representation sits between the stimulus and response in the processing chain (e.g., 1—ODD—left; Schneider, 2014). The mediated route produces response congruency effects because for congruent stimuli, the intermediate response categories from both tasks both map onto the same response key (e.g., the response categories for the stimulus 1 are ODD and LOWER, which both require a left response). Incongruent stimuli afford response categories which map onto different keys (e.g., the response categories for the stimulus "7" are ODD and HIGHER, which map to separate keys).

In the *non-mediated* route, response selection does not rely on an intermediate response category representation; rather, the target directly retrieves instances from long-term memory of the responses performed on that stimulus (Logan, 1988). This produces response congruency effects because for congruent stimuli, the targets are always associated with the same response key regardless of the task, so the retrieved instances for these stimuli will activate the same response key. For incongruent stimuli, however, the targets are associated with different response keys (e.g., left for the parity task, and right for the magnitude task), so the retrieved instances will activate different keys; the ambiguity needs to be resolved by way of the current trial's instruction (e.g., the current trial's cue).

Ascertaining which route of response selection is used can be achieved using tailored experimental manipulations (Schneider, 2015b; Schneider & Logan, 2015), which were not employed in any of the studies reported in the meta-analysis. As such, it is likely that both routes contributed to response congruency effects in the studies reported here. This is a potential limitation because we cannot conclude from our analysis that there is no age-related difference in response congruency effects in the separate routes of response selection, because we cannot be sure which was in operation. That is, there may exist age-related deficits in one route of response selection that are masked because the other route compensates during response selection, leading to no observable age-related difference. Future work should systematically examine—using the experimental manipulations proposed by Schneider and colleagues—whether there are age-related effects when each route of response selection is isolated.

Relation to Other Task Switching & Aging Findings

Our results add to the evidence of a general lack of age-related deficits on task switching. In their meta-analysis, Wasylyshyn et al. (2011) found no evidence for age-related deficits in the switch cost in task switching designs: the finding of slower RTs to task switches than to task repetitions. However, Wasylyshyn et al. (2011) did find evidence for age-related deficits in the mixing cost: slower RTs to blocks containing two different tasks compared to blocks containing just one task. There is growing evidence for no age-related deficits in other task switching effects, too. For example, successful task switching is thought to require the inhibition of recently-performed tasks (Koch, Gade, Schuch, & Philipp, 2010; Mayr & Keele, 2000). Evidence for inhibition in task switching comes from the n–2 task repetition cost: The observed slowing of RTs for ABA task switching sequences compared to CBA sequences. This cost is thought to reflect the persisting inhibition of task A in an ABA sequence. Evidence is growing that there are no age-related deficits in this effect: although Mayr (2001) found larger n–2 task repetition costs for older adults, subsequent studies have found no difference at the behavioural level (Grange & Kowalczyk, under review; Lawo & Koch, 2012; Schuch, 2016).

Conclusion

In summary, we find no evidence for age-related differences in response congruency in task switching designs. These findings sit within a wider landscape of evidence showing no age-related decline in key measures of attention and executive functioning (Verhaeghen, 2011, 2014).

References

* References marked with an asterisk were included in the meta-analysis

Altmann, E. M., & Gray, W. D. (2008). An integreated model of cognitive control in task switching. *Psychological Review, 115* , 602–639. doi: 10.1037/0033-295X.115.3.602

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67* . doi: 10.18637/jss.v067.i01

*Capeda, N. J., Kramer, A. F., & Gonzalez de Sather, J. C. M. (2001). Changes in executive control across the life span: Examination of task-switching performance. *Developmental Psychology, 37* , 715–730. doi: 10.1037/0012-1649.37.5.715

Dai, C.-T., Chang, Y.-K., Huang, C.-J., & Hung, T.-M. (2013). Exercise mode and executive function in older adults: An ERP study of task-switching. *Brain and Cognition, 83* , 153–162. doi: 10.1016/j.bandc.2013.07.007

De Jong, R. (2001). Adult age differences in goal activation and goal maintenance. *European Journal of Cognitive Psychology, 13* , 71–89. doi: 10.1080/09541440042000223

DiGirolamo, G. J., Kramer, A. F., Barad, V., Cepeda, N. J., Weissman, D. H., Milham, M. P., & McAuley, E. (2001). General and task-specific frontal lobe recruitment in older adults during executive processes: A fMRI investigation of task-switching. *Neuroreport, 12* , 2065–2071. doi: 10.1097/00001756-200107030-00054

*Eich, T. S., Parker, D., Liu, D., Oh, H., Razlighi, Q., Gazes, Y., . . . Stern, Y. (2016a). Functional brain and age-related changes associated with congruency in task switching. *Neuropsychologia, 91* , 211–221. doi: 10.1016/j.neuropsychologia.2016.08.009

*Eich, T. S., , Rakitin, B. C. & Stern, Y. (2016b). Response-conflict moderates the cognitive control of episodic and contextual load in older adults. *Journals of Gerontology: Psychological Sciences, 71* , 995–1003. doi: 10.1093/geronb/gbv046

Enriquez-Geppert, S., & Barcelò, F. (in press). Multisubject decomposition of event-related positivities in cognitive control: Tackling age-related changes in reactive control. *Brain Topography*. doi: 10.1007/s10548-016-0512-4

*Eppinger, B., Kray, J., Mecklinger, A., & John, O. (2007). Age differences in response monitoring: Evidence from ERPs. *Biological Psychology, 75* , 52–67. doi: 10.1016/j.biopsycho.2006.12.001

Fong, D.-Y., Chi, L.-K., Fuzhong, L., & Chang, Y.-K. (2014). The benefits of endurance exercise and tai chi chuan for the task-switching aspect of executive function in older adults: an ERP study. *Frontiers in Aging Neuroscience*, *6* , 295.

Frantz, J. (n.d.). *g3data (for Windows) [Computer Software]*. www.frantz.fi/software/g3data.php.

*Friedman, D., Nessler, D., Johnson, R., Ritter, W., & Bersick, M. (2008). Age-related changes in executive function: An event-related potential (ERP) investigation of task-switching. *Aging, Neuropsychology, and Cognition.*, *15* , 1–34. doi: 10.1080/13825580701533769

Gamboz, N., Borella, E., & Brandimonte, M. A. (2009). The role of switching, inhibition, and working memory in older adults? performance in the Wisconsin card sorting test. *Aging, Neuropsychology, and Cognition*, *16* , 260–284. doi: 10.1080/13825580802573045

Goffaux, P., Phillips, N. A., Sinai, M., & Pushkar, D. (2008). Neurophysiological measures of task-set switching: Effects of working memory and aging. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, *63* , 57–66. doi: 10.1093/geronb/63.2.P57

Gold, B. T., Powerll, D. K., Xuan, L., Jicha, G. A., & Smith, C. D. (2010). Age-related slowing of task switching is associated with decreased integrity of frontoparietal white matter. *Neurobiology of Aging, 31* , 512–522. doi: 10.1016/j.neurobiolaging.2008.04.005

Goschke, T. (2000). Intentional reconfiguration and involuntary persistence in task set switching. In S. Monsell & J. Driver (Eds.), *Control of Cognitive Processes: Attention and Performance XVIII* (pp. 331–356). Cambridge, MA: MIT Press.

Grange, J. A., & Houghton, G. (Eds.). (2014). *Task switching and cognitive control*. New York, NY: Oxford University Press.

Grange, J. A., & Kowalczyk, A. W. (under review). The effect of aging on inhibition in task switching: Controlling for episodic retrieval. Retrieved from https://osf.io/543wp/

Gratton, G., Wee, E., Rykhlevskaia, E. I., Leaver, E., & M, F. (2009). Does white matter matter? spatio-temporal dynamics of task switching in aging. *Journal of Cognitive Neuroscience, 21* , 1380–1395. doi: 10.1162/jocn.2009.21093

Hahn, S., Anderson, G. J., & Kramer, A. F. (2004). Age influences on multi-dimensional set switching. *Aging, Neuropsychology, and Cognition., 11* , 25–36. doi: 10.1076/anec.11.1.25.29360

Hasher, L., Lustig, C., & Zacks, R.T. (2007). Inhibitory mechanisms and the control of attention. In A. Conway, C. Jarrold, M. Kane, A.Miyake, & J. Towse (Eds.), *Variation in working memory* (pp. 227–249). New York, NY: Oxford University Press.

Hasher, L., Zacks, R. T., & May, C.P. (1999). Inhibitory control, circadian arousal, and age. In D. Gopher & A. Koriat (Eds.), *Attention and Performance XVII. Cognitive regulation of performance: Interaction of theory and application* (pp. 653–675). Cambridge, MA: MIT Press.

*Hirsch, P., Scwarzkopp, T., Declerck, M., Reese, S., & Koch, I. (2016). Age-related differences in task switching and task preparation: Exploring the role of task-set competition. *Acta Psychologica, 170* , 66–73. doi: 10.1016/j.actpsy.2016.06.008

*Huff, M. J., Balota, D. A., Minear, M., Aschenbrenner, A. J., & Duchek, J. M. (2015). Dissociative global and local task-switching costs across younger adults, middle-aged adults, older adults, and very mild Alzheimer?s disease individuals. *Psychology and Aging, 30* , 727–739. doi: 10.1037/pag0000057

*Jimura, K., & Braver, T. S. (2010). Age-related shifts in brain activity dynamics during task switching. *Cerebral Cortex, 20* , 1420–1431. doi: 10.1093/cercor/bhp206

Karbach, J., & Kray, J. (2009). How useful is executive control training? age differences in near and far transfer of task-switching training. *Developmental Science, 16* , 978–990. doi: 10.1111/j.1467-7687.2009.00846.x

Kiesel, A., Steinhauser, M., Wendt, M., Falkstein, M., Jost, K., Philipp, A., & Koch, I. (2010). Control and interference in task switching. *Psychological Bulletin, 136* , 849–874. doi: 10.1037/a0019842

Koch, I., Gade, M., Schuch, S., & Philipp, A. M. (2010). The role of inhibition in task switchinng: A review. *Psychonomic Bulletin & Review, 17* , 1–14. doi: 10.3758/PBR.17.1.1

*Kramer, A. F., Hahn, S., & Gopher, D. (1999). Task coordination and aging: Explorations of executive control processes in the task switching paradigm. *Acta Psychologica*, *101* , 339–378. doi: 10.1016/S0001-6918(99)00011-6

Kray, J. (2006). Task-set switching under cue-based versus memory-based switching conditions in younger and older adults. *Brain Research, 1105* , 83–92. doi: 10.1016/j.brainres.2005.11.016

Kray, J., Eber, J., & Lindenberger, U. (2004). Age differences in executive functioning across the lifespan: The role of verbalization in task preparation. *Acta Psychologica, 115* , 143–165. doi: 165.10.1016/j.actpsy.2003.12.001

*Kray, J., & Eppinger, B. (2006). Effects of associate learning on age differences in task-set switching. *Acta Psychologica*, *123* , 187–203. doi: 10.1016/j.actpsy.2005.12.009

Kray, J., & Feher, B. (2017). Age differences in the transfer and maintenance of practice-induced improvements in task switching: The impact of working-memory and inhibition demands. *Frontiers in Psychology, 8* , 410. doi: 10.3389/fpsyg.2017.00410

Kray, J., & Ferdinand, K., N. (2014). Task switching and aging. In J. A. Grange & G. Houghton (Eds.), *Task switching and cognitive control* (pp. 350–371). New York, NY: Oxford University Press.

Kray, J., & Lindenberger, U. (2000). Adult age differences in task switching. *Psychology and Aging, 15* , 126–147. doi: 10.1037/0882-7974.15.1.126

Kunimi, M., Kiyama, S., & Nakai, T. (2016). Investigation of age-related changes in brain activity during thedivalent task-switching paradigm using functional MRI. *Neuroscience Research, 103* , 18–26. doi: dx.doi.org/10.1016/j.neures.2015.06.011

*Lawo, V., & Koch, I. (2012). Examining age-related differences in auditory attention control using a task-switching procedure. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 69* , 237–244. doi: 10.1093/geronb/gbs107

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review*, *95*, 492–527. doi: doi:10.1037/0033-295X.95.4.492

Logan, G. D. (2003). Executive control of thought and action: In search of the wild homunculus. *Current Directions in Psychological Science, 12* , 45–48. doi: https://doi.org/10.1111/1467-8721.01223

Lucenet, J., Blaye, A., Chevalier, N., & Kray, J. (2014). Cognitive control and language across the life span: Does labeling improve reactive control? *Developmental Psychology, 50* , 1620–1627. doi: 10.1037/a0035867

Marí-Beffa, P., & Kirkham, A. J. (2014). The mixing cost as a measure of cognitive control. In J. A. Grange & G. Houghton (Eds.), *Task switching and cognitive control* (pp. 74–100). New York, NY: Oxford University Press.

*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. doi: 10.1037/0882-7974.16.1.96

Mayr, U., & Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. *Journal of Experimental Psychology: General*, *129* , 4–26. doi: http://dx.doi.org/10.1037/0096-3445.129.1.4

*Mayr, U., & Liebscher, T. (2001). Is there an age deficit in the selection of mental sets? *European Journal of Cognitive Psychology*, *13* , 47–69. doi: 10.1080/09541440042000214

Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, *22* , 1423–1442. doi: 10.1037/0278-7393.22.6.1423

Meiran, N., Chorev, Z., & Sapir, A. (2000). Component processes in task switching. *Cognitive Psychology*, *41* , 211–253. doi: 10.1006/cogp.2000.0736

*Meiran, N., Gotler, A., & Perlman, A. (2001). Old age is associated with a pattern of relatively intact and relatively impaired task-set switching abilities. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, *56* , 88–102. doi: 10.1093/geronb/56.2.P88

Monsell, S., Sumner, P., & Waters, H. (2003). Task-set reconfiguration with predictable and unpredictable task switches. *Memory & Cognition*, *31* , 327–342. doi: 10.3758/BF03194391

Perfect, T. J., & Maylor, E. A. (2000). Rejecting the dull hypothesis: The relation between method and theory in cognitive aging research. In T. J. Perfect & E. A. Maylor (Eds.), *Models of cognitive aging* (pp. 1–18). New York, NY: Oxford University Press.

Pettigrew, C., & Martin, R. C. (2016). The role of working memory capacity and interference resolution mechanisms in task switching. *Quarterly Journal of Experimental Psychology*, *69* , 2431–2451. doi: 10.1080/17470218.2015.1121282

R Core Team. (2015). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from http://www.R-project.org/

*Rey-Mermet, A. & Meir, B. (2015). Age affects the adjustment of cognitive control after a conflict: Evidence from the bivalency effect. *Aging, Neuropsychology, and Cognition, 22,* 72–94. doi:10.1080/13825585.2014.889070

*Reimers, S. & Maylor, E. A. (2005). Task switching across the life span: Effects of age on general and specific switch costs. *Developmental Psychology*, *41,* 661–671. doi:10.1037/0012-1649.41.4.661

Schneider, D. W. (2014). Modeling graded response congruency effects in task switching. *Acta Psychologica*, *153* , 160–168. doi: 10.1016/j.actpsy.2014.10.006

Schneider, D. W. (2015a). Attentional control of response selection in task switching. *Journal of Experimental Psychology: Human Perception and Performance*, *41* , 1315–1324. doi: 10.1037/xhp0000091

Schneider, D. W. (2015b). Isolating a mediated route for response congruency effects in task switching. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *41,* 235–245. doi: 10.1037/xlm0000049

Schneider, D. W., & Logan, G. D. (2015). Learning a nonmediated route for response selection in task switching. *Memory & Cognition*, *43* , 837–851. doi: 10.3758/s13421-015-0507-5

Schuch, S. (2016). Task inhibition and response inhibition in older vs. younger adults: A diffusion model analysis. *Frontiers in Cognition*, *7* , 1722. doi: https://doi.org/10.3389/fpsyg.2016.01722

Serbruyns, L., Leunissen, I., van Ruitenbeek, P., Pauwels, L., Caeyengerghs, K., Solesio-Jofre, E., . . . Swinnen, S. P. (2016). Alterations in brain white matter contributing to age-related slowing of task switching performance: The role of radial diffusivity and magnetization transfer ratio. *Human Brain Mapping*, *37* , 4084–4098.

Spieler, D., Mayr, U., & LaGrone, S. (2006). Outsourcing cognitive control to the environment: Adult-age differences in the use of task cues. *Psychonomic Bulletin & Review*, *5* , 787–793. doi: 10.3758/BF03193998

Tsai, C.-L., & Wang, W.-L. (2015). Exercise-mode-related changes in task-switching performance in the elderly. *Frontiers in Behavioral Neuroscience*, *9* , 56. doi: 10.3389/fnbeh.2015.00056

Vandierendonck, A., Liefooghe, B., & Verbruggen, F. (2010). Task switching: Interplay of reconfiguration and interference. *Psychological Bulletin*, *136* , 601–626. doi: 10.1037/a0019791

Verhaeghen, P. (2011). Aging and executive control: Reports of a demise greatly exaggerated. *Current Directions in Psychological Science*, *20* , 174–180. doi: 10.1177/0963721411408772

Verhaeghen, P. (2014). *The elements of cognitive aging*. New York, NY: Oxford University Press.

Wasylyshyn, C., Verhaeghen, P., & Sliwinski, M. J. (2011). Aging and task switching: A meta-analysis. *Psychology and Aging*, *26* , 15–20. doi: 10.1037/a0020912 Wilckens,

K. A., Woo, S. G., Erickson, K. I., & Wheeler, M. E. (2014). Sleep continuity and total sleep time are associated with task-switching and preparation in young and older adults. *Journal of Sleep Research*, *23* , 508–516. doi: 10.1111/jsr.12148

Zhu, Z., Johnson, N. F., Kim, C., & Gold, B. T. (2015). Reduced frontal cortex efficiency is associated with lower white matter integrity in aging. *Cerebral Cortex*, *25* , 138–146. doi: 10.1093/cercor/bht212

Table 1

Fit statistics of the four models for the Brinley analysis. Note: df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/condition).

Model	df	LogLik	AIC	BIC
(1) RT_{Older} ~ RE	4	9.89	-11.77	-3.81
(2) RT_{Older} ~ $RT_{Younger}$ + RE	5	54.41	-98.83	-88.88
(3) RT_{Older} ~ $RT_{Younger}$ + congruency + RE	6	54.50	-97.01	-85.08
(4) RT_{Older} ~ $RT_{Younger}$ + congruency + ($RT_{Younger}$ * congruency) + RE	7	55.18	-96.36	-82.44

Table 2

Fit statistics of the four models for the state–trace analysis. Note: df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/condition).

Model	df	LogLik	AIC	BIC
(1) $RT_{Incongruent}$ ~ RE	4	-16.47	40.95	48.90
(2) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + RE	5	68.74	-127.49	-117.54
(3) $RT_{Incongruent}$ ~ $RT_{Congruent}$+ age + RE	6	68.81	-125.62	-113.68
(4) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + age + ($RT_{Congruent}$ * age) + RE	7	70.88	-127.76	-113.84

Figures

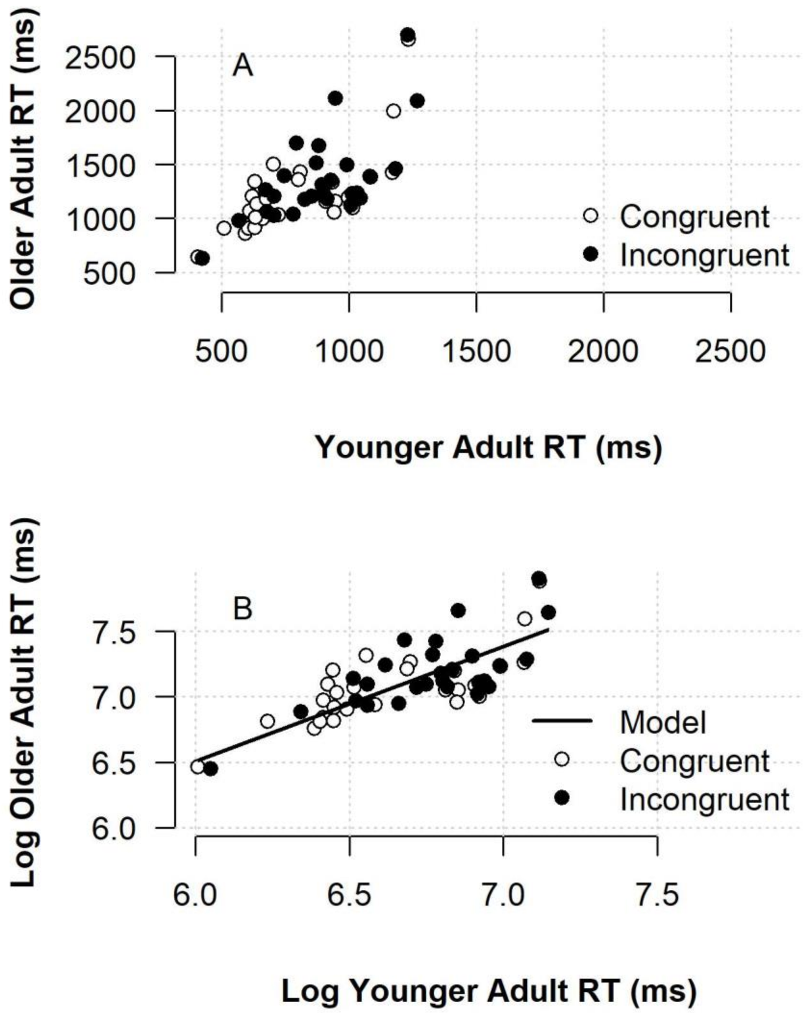

Figure 1. Brinley plot showing the relationship between young-adult response time (RT) and older-adult response time in milliseconds (ms) as a function of congruency. **Panel A.** Non-transformed data. **Panel B.** Log-transformed data. The regression line shows the fit of the best-fitting model from the model selection procedure.

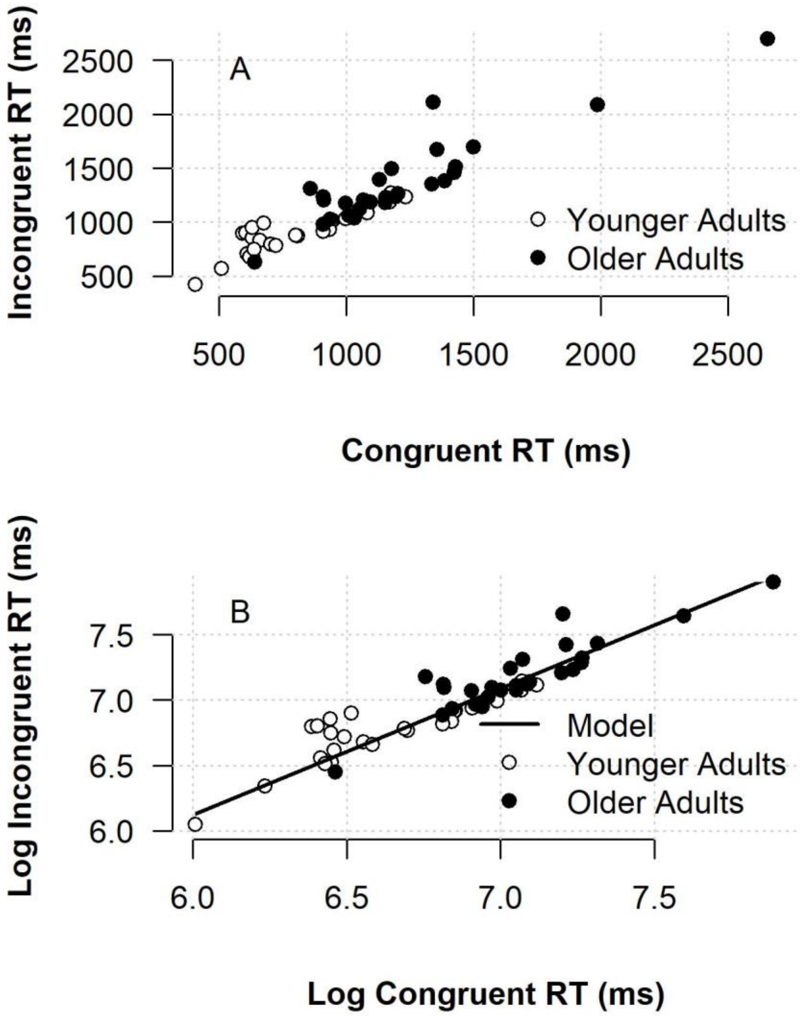

Figure 2. State–trace plot showing the relationship between congruent response time (RT) and incongruent response time in milliseconds (ms) as a function of age group. **Panel A.** Non-transformed data. **Panel B.** Log-transformed data. The regression line shows the fit of the best-fitting model from the model selection procedure.

Supplementary Material:

The Effect of Aging on Response Congruency in Task Switching:

A Meta-Analysis

James A. Grange & Raymond B. Becker

Contents

Appendix A - Study Information & Data Table

The table containing all study information and congruency data for the meta-analysis can be downloaded from the Open Science Framework at https://osf.io/3u9s2/

Appendix B - State–Trace Analysis Model Comparison

Although we prefer the model with a single-regression line in the state–trace analysis reported in the main paper, for completeness here we show the interested reader the fit of the full interaction model, which was slightly preferred by the AIC statistic. Figure B1 shows the fit of the selected model from the main analysis in Panel A (i.e., a single-regression line); for comparison, Panel B shows the fit of the interaction model. As can be seen, if present at all, the interaction is only slight.#

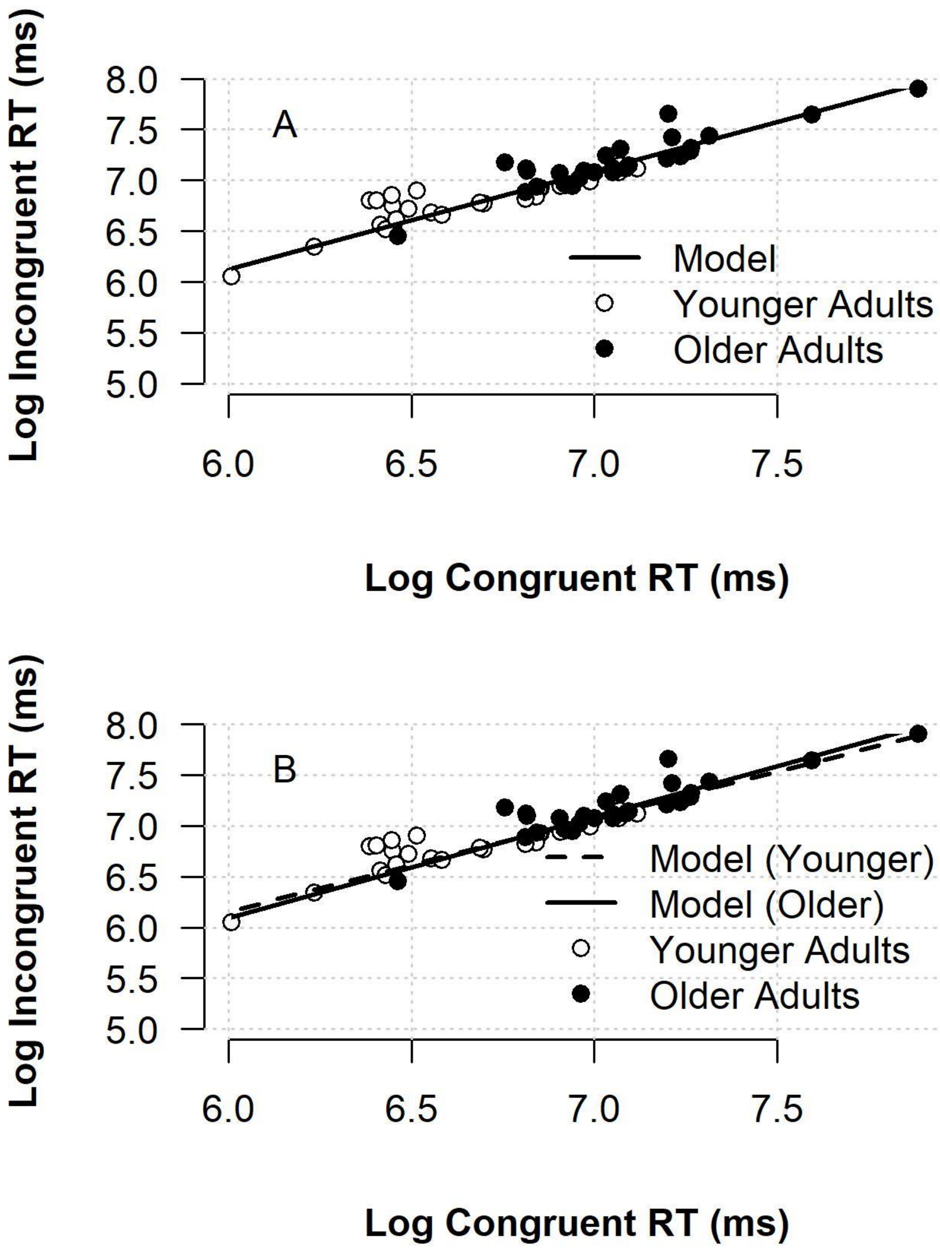

Figure B1. State–trace plot showing the relationship between log-transformed congruent response time (RT) and incongruent response time in milliseconds (ms) as a function of age group. **Panel A.** Best-fitting model from the model selection procedure in the main text. **Panel B.** The interaction model.

Appendix C - Additional Moderator Analyses

In this section, we detail the analysis conducted to explore potential moderators of the effects reported in the main body of the text. In particular, we focus on whether the mean age of the older adults and the number of trials in the study (i.e., the degree of practice experienced by participants) moderated the effects reported. The R code used to conduct these extra analyses are a component of the main analysis script available on the Open Science Framework at https://osf.io/3u9s2/.

Number of Trials in Study

For this analysis, we were interested in whether the number of trials in each study moderated the effects reported in the main text. We defined the number of trials as the total number of trials experienced by the participant, regardless of whether those trials were included in the meta-analysis or not. For example, in our meta-analysis, we only included data from so-called "mixed-blocks", where more than one task was relevant. However, many studies had so-called "pure-blocks", where just one trial was relevant for the duration of the block. Also, all studies had practice blocks to allow the participants to become familiar with the task demands. The number of trials (hereafter n_trials) was the sum of all of these trial types.

We approach this question by adding n_trials as a continuous predictor (just a main effect) to each of the four models reported in the main text (separately for the Brinley analysis and the state–trace analysis) to see whether adding this predictor alters the model competition outcome.

Brinley analysis. N_trials was centered and scaled before being added as a main effect to the linear mixed models reported in Table 1 of the main paper. The new model specifications and fit statistics are shown in Table C1.

Table C1

Fit statistics of the four models for the Brinley analysis with number of trials (n_trials) added as a continuous predictor. Note: df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/experiment).

Model	df	LogLik	AIC	BIC
(1) RT_{Older} + n_trials ~ RE	5	11.26	-12.51	-2.57
(2) RT_{Older} ~ $RT_{Younger}$ + n_trials + RE	6	54.43	-96.87	-84.93
(3) RT_{Older} ~ $RT_{Younger}$ + congruency + n_trials + RE	7	54.54	-95.07	-81.15
(4) RT_{Older} ~ $RT_{Younger}$ + congruency + n_trials + ($RT_{Younger}$ * congruency) + RE	8	55.20	-94.40	-78.49

The AIC and BIC fit-statistics both converge on selecting Model 2 as the best-fitting model, which is in agreement with the outcome of the analysis in the main text of the paper (i.e., that adding congruency does not improve the model fit).

This was confirmed with likelihood ratio tests. The model with RT-older being predicted from RT-younger and n_trials (Model 2) had a better goodness of fit compared to a model with just the random effects and n_trials model (Model 1), $\chi(1) = 86.35$, $p < .001$. Adding a main effect of congruency (Model 3) did not improve the goodness of fit, $\chi(1) = 0.21$, $p = .65$, nor did adding a main effect of congruency and its interaction with RT–younger (Model 4), $\chi(2) = 1.53$, $p = .46$. The best-fitting model (Model 2) had an intercept of 1.25 (SE = 0.316), and a RT-younger coefficient of b = 0.877 (SE = 0.047) and n_trials coefficient of b = -0.008 (SE = 0.041). The large standard error of the n_trials predictor relative to its coefficient suggests it is not adding to the model's prediction.

In a second stage, we were interested in whether adding n_trials to the model (i.e., Model 2 in Table C1) significantly improved the fit compared to a model without n_trials (i.e., Model 2 from Table 1 in the main paper). A likelihood ratio test of these two models found no significant improvement of fit by adding n_trials to the model, $\chi(1) = 0.04$, $p = .84$. These analyses converge on the conclusion that the number of trials does not moderate the effect reported in the paper for the Brinley analysis.

State–trace analysis. N_trials was centered and scaled before being added as a main effect to the linear mixed models reported in Table 2 of the main paper. The new model specifications and fit statistics are shown in Table C2.

Table C2

Fit statistics of the four models for the state–trace analysis with number of trials (n_trials) added as a continuous predictor. Note: age = the age group of the participant (younger vs. older); df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/experiment).

Model	df	LogLik	AIC	BIC
(1) $RT_{Incongruent}$ + n_trials ~ RE	5	-14.02	38.04	47.98
(2) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + n_trials RE	6	68.77	-125.53	-113.60
(3) $RT_{Incongruent}$ ~ $RT_{Congruent}$+ age + n_trials + RE	7	68.82	-123.64	-109.72
(4) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + age + n_trials + ($RT_{Congruent}$ * age) + RE	8	70.89	-125.79	-109.88

As in the main paper, the BIC statistic prefers a model without the age group of the participant as a predictor (Model 2), and the AIC statistic appears to prefer an interaction model. Inspection of the AIC values shows little difference between the full interaction model (Model 4, AIC = -125.79) and the model without the age group predictor (Model 2, AIC = -125.53). As in the main paper, we see no reason to not prefer the simpler Model 2 which does not have age group as a predictor.

This was confirmed using likelihood ratio tests. The model with RT-incongruent predicted from RT-congruent and n_trials (Model 2) had a better goodness of fit compared to a model with just the random effects and n_trials model (Model 1), $\chi(1) = 165.57$, $p < .001$. Adding a main effect of age (Model 3) did not improve the fit, $\chi(1) = 0.11$, $p = .74$, nor did adding a main effect of RT-congruent together with its interaction with age (Model 4), $\chi(2) = 4.26$, $p = .12$. The best-fitting model (Model 2) had an intercept = 0.32 (SE = 0.138), and RT-congruent coefficient b = 0.967 (SE = 0.020) and n_trials coefficient of b = 0.005 (SE = 0.024). The large standard error of the n_trials predictor relative to its coefficient suggests it is not adding to the model's prediction.

In a second stage, we were interested in whether adding n_trials to the model (i.e., Model 2 in Table C2) significantly improved the fit compared to a model without n_trials (i.e., Model 2 from Table 2 in the main paper). A likelihood ratio test of these two models found no significant improvement of fit by adding n_trials to the model, $\chi(1) = 0.04$, $p = .83$. These analyses converge on the conclusion that the number of trials does not moderate the effect reported in the paper for the state–trace analysis.

Mean Age of Older Adults

We approach the question of whether age moderates the effects reported in the main body of the paper by adding the mean age of the older adults (hereafter mean_age) in each study as a continuous predictor (just a main effect) to each of the four models reported in the main text (separately for the Brinley analysis and the state–trace analysis) to see whether adding this predictor alters the model competition outcome.

Brinley analysis. Mean_age was centered before being added as a main effect to the linear mixed models reported in Table 1 of the main paper. The new model specifications and fit statistics are shown in Table C3.

Table C3

Fit statistics of the four models for the Brinley analysis with the average age of the older adults (mean_age) added as a continuous predictor. Note: df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/experiment).

Model	df	LogLik	AIC	BIC
(1) RT_{Older} + mean_age ~ RE	5	11.81	-13.61	-3.67
(2) RT_{Older} ~ $RT_{Younger}$ + mean_age + RE	6	57.08	-102.17	-90.23
(3) RT_{Older} ~ $RT_{Younger}$ + congruency + mean_age + RE	7	57.23	-100.47	-86.55
(4) RT_{Older} ~ $RT_{Younger}$ + congruency + mean_age + ($RT_{Younger}$ * congruency) + RE	8	57.86	-99.73	-83.82

The AIC and BIC fit-statistics both converge on selecting Model 2 as the best-fitting model, which is in agreement with the outcome of the analysis in the main text of the paper (i.e., that adding congruency does not improve the model fit). This was confirmed with likelihood ratio tests. The model with RT-older being predicted from RT-younger and mean_age (Model 2) had a better goodness of fit compared to a model with just the random effects and mean_age model (Model 1), $\chi(1) = 90.57$, $p < .001$. Adding a main effect of congruency (Model 3) did not improve the goodness of fit, $\chi(1) = 0.30$, $p = .58$, nor did adding a main effect of congruency and its interaction with RT–younger (Model 4), $\chi(2) = 1.56$, $p = .46$. The best-fitting model (Model 2) had an intercept of 1.28 (SE = 0.309), and a RT-younger coefficient of b = 0.871 (SE = 0.046) and mean_age coefficient of b = 0.021 (SE = 0.008). The small standard error of the mean_age predictor relative to its coefficient suggests it is adding to the model's prediction.

In a second stage, we were interested in whether adding mean_age to the model (i.e., Model 2 in Table C3) significantly improved the fit compared to a model without mean_age (i.e., Model 2 from Table 1 in the main paper). A likelihood ratio test of these two models found a significant improvement of fit by adding mean_age to the model, $\chi(1) = 5.34$, $p = .02$. This analysis suggests that—whilst the model fit significantly improves—adding mean_age to the model does not change the conclusion that the predictor congruency does not add to the predictive fit of the model; this is in line with the conclusions drawn in the main paper.

State–trace analysis. Mean_age was centered and scaled before being added as a main effect to the linear mixed models reported in Table 2 of the main paper. The new model specifications and fit statistics are shown in Table C4.

Table C4

Fit statistics of the four models for the state–trace analysis with the average age of the older adults (mean_age) added as a continuous predictor. Note: age = the age group of the participant (younger vs. older); df = degrees of freedom; LogLik = log likelihood; RT = response time; RE = "random effects". All random effects were specified (in lme4 syntax) as (1|study/experiment).

Model	df	LogLik	AIC	BIC
(1) $RT_{Incongruent}$ + mean_age ~ RE	5	-15.61	41.22	51.16
(2) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + mean_age + RE	6	68.79	-125.57	-113.64
(3) $RT_{Incongruent}$ ~ $RT_{Congruent}$+ age + mean_age +RE	7	68.84	-123.68	-109.76
(4) $RT_{Incongruent}$ ~ $RT_{Congruent}$ + age + mean_age + ($RT_{Congruent}$ * age) + RE	8	70.94	-125.87	-109.96

As in the main paper, the BIC statistic prefers a model without age group as a predictor (Model 2), and the AIC statistic appears to prefer an interaction model. Inspection of the AIC values shows little difference between the full interaction model (Model 4, AIC = -125.87) and the model without the main effect of age group (Model 2, AIC = -125.57). As in the main paper, we see no reason to not prefer the simpler Model 2.

This was confirmed using likelihood ratio tests. The model with RT-incongruent predicted from RT-congruent and mean_age (Model 2) had a better goodness of fit compared to a model with just the random effects and mean_age model (Model 1), $\chi(1) = 168.79$, $p < .001$.

Adding a main effect of age group (Model 3) did not improve the fit, $\chi(1) = 0.11$, $p = .74$, nor did adding a main effect of RT-congruent together with its interaction with age group (Model 4), $\chi(2) = 4.30$, $p = .12$. The best-fitting model (Model 2) had an intercept = 0.32 (SE = 0.138), and RT-congruent coefficient b = 0.967 (SE = 0.020) and mean_age coefficient of b = -0.001 (SE = 0.005). The similarity of the standard error of the mean_age predictor and its coefficient suggests it is not adding to the model's prediction.

In a second stage, we were interested in whether adding mean_age to the model (i.e., Model 2 in Table C4) significantly improved the fit compared to a model without mean_age (i.e., Model 2 from Table 2 in the main paper). A likelihood ratio test of these two models found no significant improvement of fit by adding mean_age to the model, $\chi(1) = 0.09$, $p = .77$. These analyses converge on the conclusion that the mean age of older adults does not moderate the effect reported in the paper for the state–trace analysis.