The effect of practice on n–2 repetition costs in set switching (Revision 1)

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Abstract

Inhibition in set switching is inferred from so-called n–2 repetition costs: slower response times to ABA sequences compared to CBA sequences (where A, B, and C are arbitrary labels for different tasks). These costs are thought to reflect the persisting inhibition of task A when it was disengaged recently (as is the case in an ABA sequence). In this study we were interested in whether more inhibition may be required when the tasks are relatively novel. To this end, we examined the effect of practice on the n–2 repetition cost in nine participants across five experimental sessions, with 1,222 trials performed in each session. The results show a clear reduction in the n–2 repetition cost, being altogether absent from the final sessions. Such a reduction is predicted by both: (a) a recent computational model of the n–2 repetition cost (Grange, Juvina, & Houghton, 2013) due to the gradual strengthening of task-related memory elements with practice to the point where inhibition has less impact; and (b) prior work showing smaller n–2 repetition costs with greater cue–target association strength (Houghton, Pritchard, & Grange, 2009). In this paper, we integrate these two theoretical derivations by extending our computational model, which fit the current data—at the mean level, block level, and individual-subject (i.e., individual differences) level—well.

Keywords: Task switching; inhibition; ACT-R; computational model

1. Introduction

The human environment is increasingly busy, with many possible tasks competing for our attention at any given time. Sat at a computer, for example, there are a plethora of tasks that could be selected (e.g. writing, Internet-browsing, playing online chess etc.). How are humans able to select the goal-relevant task (e.g. writing a manuscript) in the face of so many competitors? Once selected, how is the task maintained in the focus of attention, so that competing tasks do not interfere with ongoing performance? How is it that, when no longer goal-relevant, tasks can be switched quickly and efficiently?

The so-called task switching paradigm (Grange & Houghton, 2014; Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010) has provided much insight into the cognitive processes thought to enable successful maintenance and flexible shifting of task-sets (the mental representation of the task to perform; Logan & Gordon, 2001). In this paradigm, participants typically must rapidly switch between simple cognitive tasks on bivalent stimuli (e.g. odd/even and magnitude judgments on number stimuli). One component process thought to aid task switching is the inhibition of competing task-sets (Koch, Gade, Schuch, & Philipp, 2010; Mayr & Keele, 2000). When a task is required, the task-set must become active in working memory in order to be acted upon. However, such activation is hindered by the still-active representation from the previous trial; thus activation of the *current* task-set is thought to be coupled with the inhibition of the *previous* task-set (Mayr & Keele, 2000).

Evidence for inhibition in task switching comes from the backward inhibition paradigm (Mayr & Keele, 2000) where participants switch between three potential tasks. It has been consistently shown that response times and errors are increased returning to a task after one intermediate task (e.g. AB*A*) compared to returning to a task not-so-recently performed (e.g. CB*A*). This *n–2 repetition cost* is thought to reflect the persisting inhibition of task A, which hampers its re-activation when required soon after its inhibition (as in an ABA sequence). Inhibition in task switching has been shown to act on many different levels of the task-set, targeting those aspects of the trial-structure that generate the greatest inter-trial conflict (Houghton et al., 2009): the n–2 repetition cost is modulated by altering cue/preparation-related processes (Gade & Koch, 2014; Grange & Houghton, 2009, 2010b, 2011; Houghton et al., 2009; Scheil & Kleinsorge, 2014), stimulus-related processes (Sdoia & Ferlazzo, 2008) and response-related processes (Philipp, Jolicoeur, Falkenstein, & Koch, 2007; Schuch & Koch, 2003).

Although much is known about the n–2 repetition cost, there are still some fundamental questions to be addressed. One such question we focus on in the current paper is whether more inhibition is required when the tasks being performed are relatively novel; that is, we were interested in whether there was any modulation of the n–2 repetition cost with extended practice. Recent studies have examined the effect of practice on standard task switching measures. For example, Stoet and Snyder (2007) and Berryhill and Hughes (2009) investigated the effect of practice on switch costs (the RT cost to task switches compared to task repetitions): Berryhill and Hughes (2009) found the cost was reduced, but not eliminated; Stoet and Snyder (2007) found a reduction of the cost in two naiive participants, but a slight *increase* for two non-naiive participants. Strobach, Liepelt, Schubert, and Kiesel (2012) also found the switch cost reduced, but was not eliminated after practice;

however, these authors observed that the mixing cost—the slower RT to a task repetition trial in a switching block compared to a task repetition trial when only that task is possible (i.e. a pure block)—was fully eliminated after practice. These results seem to converge on the finding that the switch cost cannot be eliminated even after extensive practice, suggesting it reflects a core limitation to cognitive flexibility. However, none of these studies investigated the n–2 repetition cost.

Indeed, upon considering prior work in this area, we derived—on the basis of two theoretical reasons—a clear prediction of a reduction of the n–2 repetition cost with extended practice. One aspect of theory that predicts a reduction of the cost with practice regards the practice-driven reduction of conflict in working memory when switching, due to automatisation of establishing the relevant attentional set (i.e., cue–target translation; see Houghton et al., 2009); the other arises from a recent computational model of inhibition in set switching (Grange et al., 2013) whereby increased practice of a task raises the resting activation levels of task-related memory elements, which over-rides short-term inhibition. We discuss each in turn below.

1.1. Automatisation of cue–target translation processes

One reason to predict a reduction of the n–2 repetition cost with practice stems from the work of Houghton and colleagues (Grange & Houghton, 2010b; Houghton et al., 2009) who suggested that inhibition in a set switching context can be triggered by cue-related conflict in working memory (WM) when establishing the relevant attentional set. In their target-detection set-switching paradigm (similar to that of Mayr & Keele, 2000), participants were presented with four potential target ovals, with each differing on a unique visual property (e.g. one was angled, one was shaded, and one had a thick border; one was neutral and upright and served as a distractor). Participants were presented with a cue which signalled which target to search for on that trial (for example, a "square" cue might mean search for the shaded oval). Houghton and colleagues (2009) argued that participants must use the cue to activate a representation (i.e. attentional set) of which target to search for, a process they called cue–target translation. When the relevant target switches, the representation formed on the previous trial generates conflict in WM with the representation required on the current trial, triggering inhibition of the prior representation.

Supporting evidence comes from manipulating the *transparency* of the cue–target relationship; that is, the degree to which the cue exogenously provides the representation required to find the relevant target (Grange & Houghton, 2010a). For example, a cue–target relationship with low transparency would have no pre-experimental association with its paired target (e.g. a square cue being paired with a shaded oval target) whereas a highly-transparent cue–target relationship the cue would share some of the properties of the to-be-located target (e.g. a shaded rectangular cue being paired with a shaded oval target). Decreasing cue–target transparency increases the effort required to form an active representation of the target, increasing the amount of potential conflict in WM when a switch is required. For maximally-transparent cue–target pairings, very little (if any) cue–target translation is required, and thus little conflict arises in WM during a switch, triggering no/less inhibition. Across several studies, Houghton and colleagues have shown that the magnitude of the n–2 repetition cost is inversely related to the transparency of the cue–target relationship, being altogether absent when highly-transparent cue–target pairings are

used (Grange & Houghton, 2009, 2010b, 2011; Grange et al., 2013; Houghton et al., 2009).

Such an account would predict a reduction of n–2 repetition cost with extended practice due to the gradual automisation of cue–target translation processes. Using non-transparent cue–target pairings, cue–target translation is initially slow and effortful, requiring considerable work in WM to activate a target representation (what Logan, 1988, might call an "algorithmic" process); thus, when a switch occurs, there is more in WM that can generate conflict (and hence inhibition). With practice, however, this slow process can be replaced by a fast automatic retrieval process, whereby prior instances of the cue–target relationship can be directly retrieved from long-term memory with little effort. Thus, when automated, cue–target translation requires less effort, and generates less conflict in WM when switching. With practice, non-transparent cue–target pairings might therefore behave like highly transparent cue–target pairings, because the cue can directly retrieve the target pairing. This is a natural prediction from our prior work, investigating how cue–target transparency modulates inhibition in set switching.

1.2. Predictions from a computational model of inhibition

In a previous paper (Grange et al., 2013), we presented a computational model to account for n–2 repetition costs and benefits in set switching. This model was implemented in the ACT-R cognitive architecture (Anderson, 2007) and integrates other previous related work (Juvina & Taatgen, 2009; Lebiere & Best, 2009). This model was able to account for n–2 repetition costs by using the standard cognitive mechanisms embedded in ACT-R (e.g., memory activation due to frequency and recency of use) and a newly added inhibition mechanism (Lebiere & Best, 2009)[1]. In the ACT-R model of the target-detection paradigm of Houghton et al. (2009), correct performance on an individual trial required successive retrieval of "chunks" of information from declarative memory. For example, when presented with a square cue, the model needs to retrieve a chunk from declarative memory that represents the target that is paired with that cue. In ACT-R, a retrieval request returns the most active chunk; thus, the system must ensure that the correct chunk is the most active. The speed of retrieving a chunk is inversely related to its activation: highly active chunks are retrieved quickly and accurately.

In ACT-R, the total activation of a chunk is governed by the current context (e.g. through spreading activation from presented cues) as well as its base-level learning activation (BLL), which reflects the degree of practice with a particular chunk. It assumes that once

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[1] The model was not designed to account for standard task switching effects, such as the switch cost and its reduction with increased preparation. Indeed, in a standard task switching experiment (i.e. comparing task switch versus task repetition sequences) the model of Grange et al. (2013) would actually predict repetition costs (rather than the benefits observed) because in the model the most recently performed task is inhibited. (Although, it should be noted that the model can easily account for both n–1 repetition benefits and n–2 repetition costs if we assume a fast short-term store independent of long term memory.) However, in backward inhibition paradigms, no task repetitions occur; it has been shown by Philipp and Koch (2006) that the n–2 repetition cost is reduced/eliminated when immediate task repetitions are possible. It might be that when no task repetitions occur (i.e., there is no benefit of repetition priming) the cognitive systems utilises a strategy of automatically inhibiting just-performed tasks (although the mechanism by which this strategy is adopted is not modelled by Grange et al.). It should also be noted that models that *do* account for standard task switching effects (e.g., Altmann & Gray, 2008; Schneider & Logan, 2005) cannot account for n–2 repetition costs. Thus, although the model is far from complete, it does account for empirical effects extant models do not.

a chunk is activated, its activation will begin to decay as a power function of time, making it gradually less accessible. Formally, the base-level activation A of chunk i is governed by

$$A_i = ln \sum_{j=1}^{n} t_j^{-d} \tag{1}$$

where ln is the natural logarithm, t_j is the time since the jth presentation of that chunk, and d is a decay parameter. As this equation would predict an n–2 repetition benefit (see Grange et al., 2013), to model n–2 repetition costs, Grange et al. (2013) utilised a short-term inhibitory mechanism of Lebiere and Best (2009) which is subtracted from the total BLL (Equation 1), and only considers the most recent presentation of a chunk (cf., Equation 1). This short-term inhibitory input, γ, is given by

$$\gamma = ln \left(1 + \left(\frac{t_n}{t_s} \right)^{-d_s} \right) \tag{2}$$

where t_n is the time since the most recent reference to a chunk, t_s is an inhibition scaling parameter, and d_s is an inhibition-decay parameter. Thus, total activation is

$$A_i = ln \sum_{j=1}^{n} t_j^{-d} - \gamma \tag{3}$$

An interesting prediction that arises from this model is that the n–2 repetition cost should reduce with practice because the frequency component of activation (i.e. base-level learning, Equation 1) overpowers the short-term inhibition component (γ). In other words, extensive practice (i.e., frequency of use) strengthens memories to the point where inhibition (which is not a function of frequency) has relatively smaller and smaller impact. To demonstrate the *a priori* predictions of this model, we conducted simulations utilising the experimental procedures presented in the present paper (i.e. 5 sessions of 1,222 trials) using the parameters from the model in Grange et al. (2013). The model's predictions are shown in Figure 1, and indeed show a reduction of n–2 repetition cost with practice.

1.3. Summary

To summarise, we have derived two clear theoretical reasons to expect a decline in n–2 repetition cost with extended practice in the set switching paradigm of Houghton et al. (2009). In the following section we report an experiment which tested this prediction. To anticipate the findings, we do indeed find a clear reduction of the n–2 repetition cost with practice. In the General Discussion, we discuss these results in light of our theoretical derivations. In particular, we extend the model of Grange et al. (2013) to include gradual strengthening of cue–target associations with practice. This increasing cue–target association strength is one way to formalise the cue–target translation hypothesis of Houghton et al. (2009), and was necessary for the model to fit the human data satisfactorily.

Based on the modelling presented in the General Discussion, we suggest that the reduction of the n–2 repetition cost with practice in this paradigm is caused by both automisation of cue–target translation *and* the gradual increase of base-level activation of memory elements.
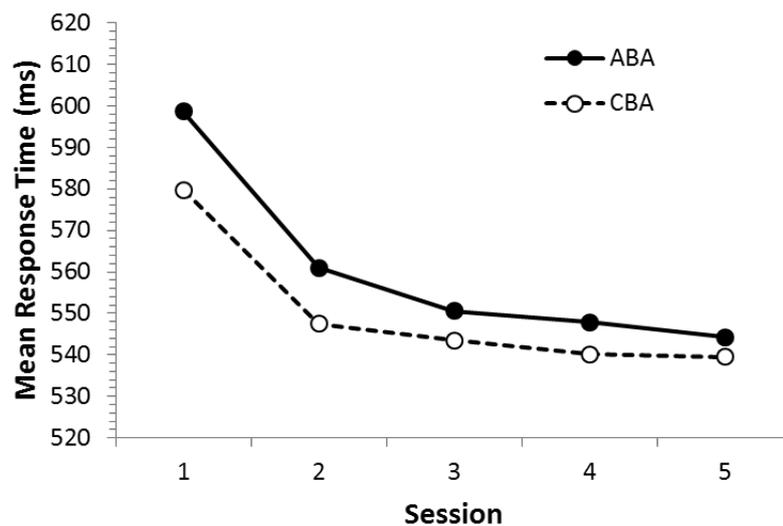
Figure 1

2. Method

2.1. Participants

10 participants were recruited from the School of Psychology at Keele University in exchange for £30 (£6 per session). One participant was removed due to average error rate above 10%.[2]

2.2. Apparatus & Stimuli

Stimuli were presented on a 17-inch CRT monitor attached to a PC running E-Prime (v. 2.0) experimental software. Responses were collected with a 1-ms precise USB keyboard. The target display consisted of the presentation of four ovals (6 centimeters [cm] in height; one had a width of 3.5cm, and the other three had widths of 2.3cm). Each target differed on a visual property: one was shaded in gray; one had a thickened black border; one was angled; one was neutral and upright, merely serving as a distractor. The three potential cues were a square, a triangle, and an octagon (each with a height and width of 4cm). Cues and targets were presented in grayscale on a white background.

2.3. Procedure

Participants were tested individually across five separate sessions, each separated by a day. Each session consisted of 10 blocks of 122 trials, preceded by a small warm-up session of 16 trials. Thus, each participant took part in 6,100 experimental trials across all sessions. A trial began with a centrally positioned cue for 500ms, which was then removed and replaced by a blank screen for 250ms; after this, the four target items were displayed,

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[2]The qualitative pattern of results remains as reported when we include this subject in the analysis, except where noted in footnote 3. As the exclusion criteria of accuracy > 90% was decided a priori, we keep this participant removed from the analysis.

with one target centered in each quadrant of the screen (target location was randomised on every trial). The participants' task was to respond to the location of the target that was paired with the cue presented making a spatially-congruent response: upper left response = D; upper right response = J; lower left response = C; lower right response = N. Participants were asked to use the index and middle finger of both hands to make their responses, and to respond as quickly and as accurately as possible. The cue–target pairings were as follows: square cue = shaded oval; triangle cue = bordered oval; octagon cue = angled oval. Once a response was registered, the targets were removed and a blank screen was displayed for 500ms, after which a new cue was presented. Cue selection was random with the constraint no repetition could occur. Set sequences were coded online by the computer program as either n–2 repetitions (i.e., ABA sequences) or n–2 switches (CBA sequences). No error feedback was provided.

2.4. Design

The experiment manipulated two independent variables in a fully-related design, with the factors task *sequence* (ABA vs. CBA) and experimental *session* (sessions 1–5). The dependent variables were response time (in milliseconds, ms) and percent error.

3. Results

The raw data was trimmed before analysis by removing the first two trials from each 122-trial block; for the response time analysis, error trials and the two trials following an error were also removed. The response time data can be seen in Figure 2 (left panel), and the error rates are shown in Table 1. Although the analysis focuses on n–2 repetition costs per experimental session, Figure 3 (upper panel) plots average n–2 repetition costs per 122-trial block of the experiment (recall each session comprised ten 122-trial blocks). This provides a finer-grained overview of the dynamics of n–2 repetition cost with practice.

3.1. Error rates

Table 1
Mean error rates (%) and their 95% confidence intervals (in square brackets) for ABA and CBA sequences across all five sessions.

	Sequence	
Session	ABA	CBA
1	2.44 [1.15, 3.62]	2.30 [0.95, 3.63]
2	2.74 [1.52, 3.97]	2.20 [0.94, 3.46]
3	2.84 [1.15, 4.54]	2.79 [1.34, 4.24]
4	3.29 [1.64, 4.94]	2.70 [1.45, 3.96]
5	3.48 [1.29, 5.67]	3.73 [2.11, 5.36]

There was no effect of sequence in the error data [$F(1,8) = 1.17$, $p = .31$, $\eta_p^2 = .13$]; the mean difference between ABA and CBA sequences was very small (0.22%, 95% CI [-0.25, 0.68]). There was a slight increase in mean errors with session [$F(4,32) = 2.49$,

$p = .06$, $\eta_p^2 = .24$]; mean differences were 0.11% [-0.65, 0.33] for session 1–2, 0.34% [-0.38, 1.06] for session 2–3, 0.18% [-0.72, 1.07] for session 3–4, and 0.61% [-0.03, 1.26] for session 4–5[3]. There was no clear modulation of n–2 repetition cost across session [$F(4,32) = 1.32$, $p = .29$, $\eta_p^2 = .14$]: the cost was 0.14% [-0.57, 0.86] for session 1, 0.54% [0.03, 1.06] for session 2, 0.06% [-0.82, 0.93] for session 3, 0.59% [-0.12, 1.30] for session 4, and -0.26% [-1.27, 0.76] for session 5.

3.2. Response Times

There was a main effect of sequence, with an n–2 repetition cost of 14ms[4] [2, 26] [$F(1,8) = 6.81$, $p = .03$, $\eta_p^2 = .46$]. There was also a general reduction of RT with session [$F(4,32) = 20.44$, $p < .001$, $\eta_p^2 = .72$]; there was a large reduction in RT between sessions 1–2 (142ms [75, 209]), but only modest/small reductions in RT between sessions 2–3 (31ms [-2, 63]), sessions 3–4 (12ms [-19, 43]) and sessions 4–5 (12ms [-8, 32])[5].

There was also a significant interaction of sequence and session [$F(4,32) = 5.07$, $p = .003$, $\eta_p^2 = .39$]: the n–2 repetition cost was 41ms [4, 78] for session one, 13ms [2, 24] for session two, 10ms [-2, 21] for session three, 5ms [-2, 13] for session four, and 1ms [-12, 13] for session five. This reduction can be seen in more fine-grained detail in Figure 3 (upper panel), which plots n–2 repetition costs as a function of each 122-trial block across the whole experiment (of which there were 50).

3.2.1. Proportion analysis. It remains possible that the reduction of the n–2 repetition cost was an artifact of the observed decrease in overall RT with increased practice. That is, it is plausible that the n–2 repetition cost is a fixed proportion of overall RT for that particular session. Although it has been shown that the n–2 repetition cost is

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[3]This increase in errors is significant if we include the removed participant [$F(4,36) = 3.36$, $p = .02$, $\eta_p^2 = .27$]

[4]In exploratory analysis, we also looked at whether the current task (e.g., "Angled task", "Border task", and "Shaded task") interacted wih any other independent variables. Thus, "task" was added as an additional factor in the analysis. There was no main effect of task [$F(1,8) = 1.45$, $p = .26$, $\eta_p^2 = .15$], but task did interact with sequence [$F(1,8) = 4.65$, $p = .026$, $\eta_p^2 = .37$]; n–2 repetition cost was 23ms for the angled task, 18ms for the border task, and 0ms for the shaded task. Task did not interact with session [$F(1,8) = 1.59$, $p = .15$, $\eta_p^2 = .17$], and did not modulate the sequence by session interaction [$F(1,8) = 1.60$, $p = .14$, $\eta_p^2 = .17$]. It is not clear what is driving this effect of task on the n–2 repetition cost, or indeed whether it replicates (as this was discovered by post-hoc exploratory analysis). This remains an interesting question to explore in future work. We are grateful to Iring Koch for suggesting this analysis.

[5]We also conducted exploratory analysis investigating whether response repetitions from n–1 to n modulated the n–2 repetition cost, and/or the reduction of n–2 repetition cost with practice (thanks to Iring Koch for suggesting this analysis). We coded the current trial as either a response-repetition (i.e., the target is in the same location at n–1 and n) or a response switch. There was a main effect of response repetition [$F(1,8) = 15.62$, $p = .004$, $\eta_p^2 = .66$], with slower responses for response repetitions (537ms) than for response switches (518ms). Response repetition did not interact with sequence [$F(1,8) = 1.86$, $p = .21$, $\eta_p^2 = .19$], session [$F(1,8) = 0.77$, $p = .56$, $\eta_p^2 = .09$], and did not modulate the sequence by session interaction [$F(1,8) = 0.47$, $p = .76$, $\eta_p^2 = .06$]. In standard task switching designs, it has been shown that response repetitions lead to benefits if the task repeats, but costs if the task switches (as is the case in the current design); this cost has been explained with reference to a self-inhibition mechanism targeting the just-executed response (Druey, 2014). However, caution must be employed interpreting this finding in our design; due to the randomization of target location among four possible locations, response (target) repetitions only occur with $p=.25$. Thus, the slowing found for response-repetitions could be explained by expectancy violations, or the relative novelty of response repetition.
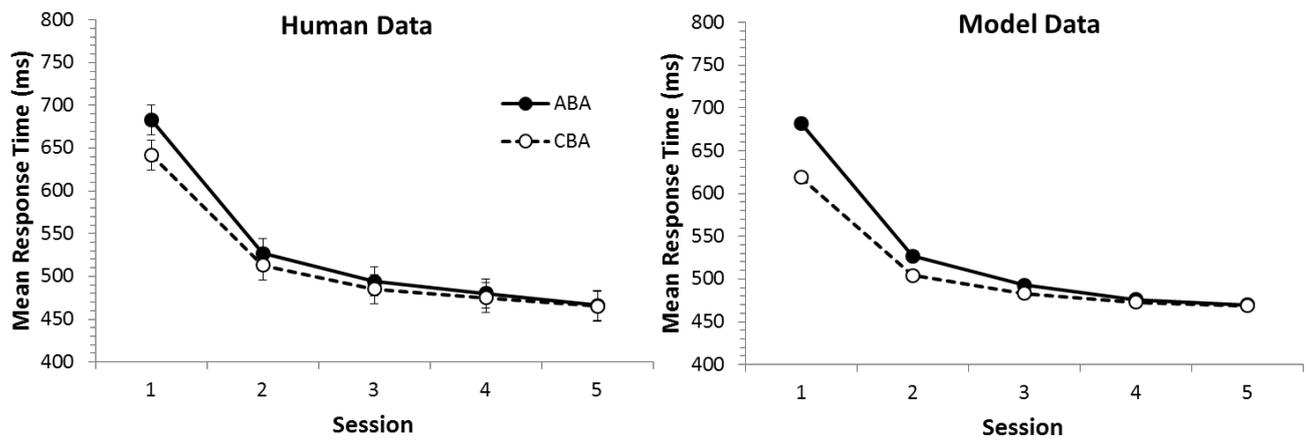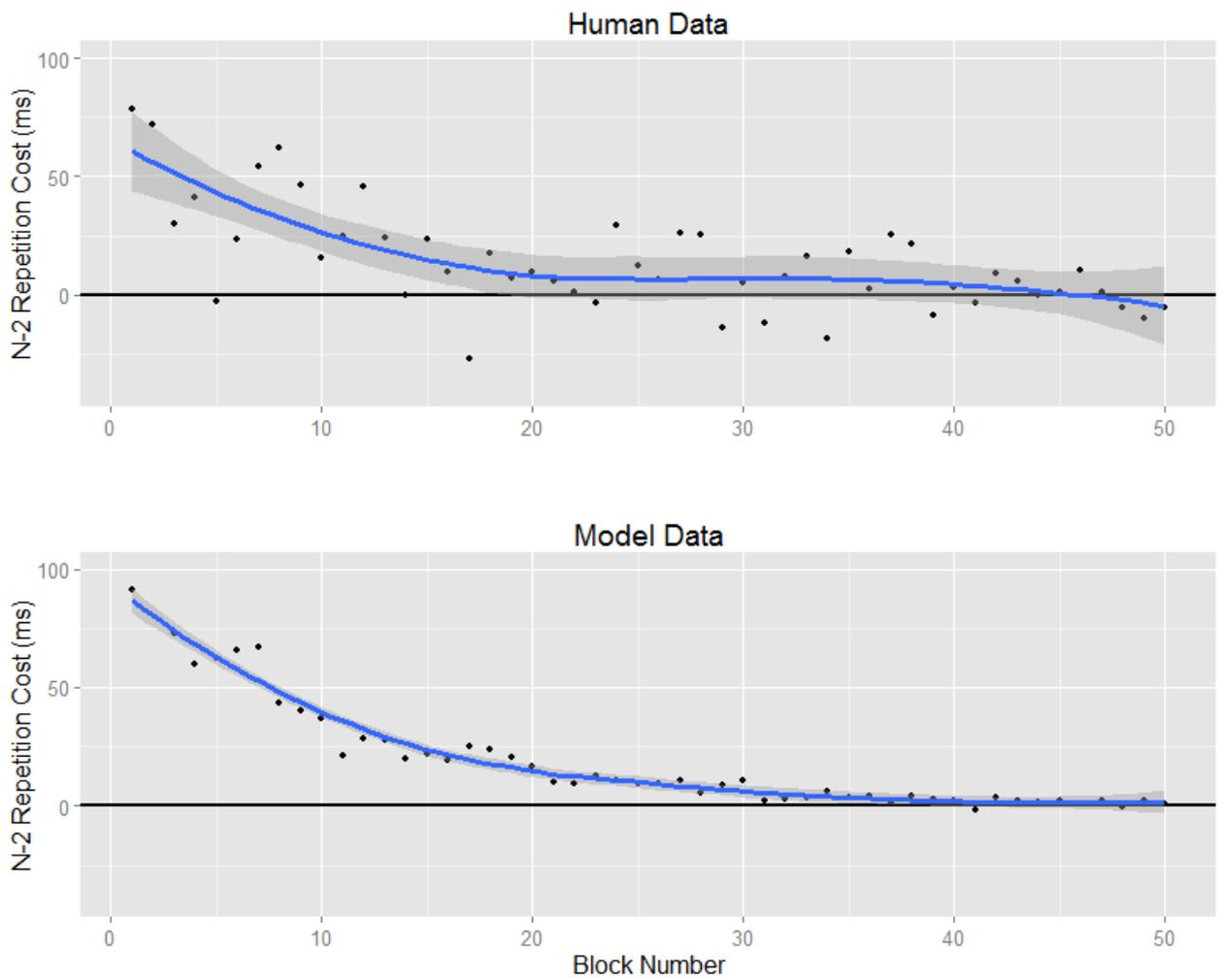
Figure 2

Figure 3

not clearly related to speed of responding (see for example Experiment 2a of Houghton et al., 2009), we wanted to address this possibility formally.

Therefore, n–2 repetition costs were calculated for each session as a proportion score of response time for that session by the following transformation (e.g. Grange, Lody, & Bratt, 2012):

$$Proportion = \frac{(RT_{ABA} - RT_{CBA})}{RT_{CBA}} \tag{4}$$

which scales the n–2 repetition cost to a suitable control RT (i.e. RT_{CBA}). The proportion n–2 repetition cost was moderate for session one (0.06 [0.01, 0.11]) and session two (0.03 [0.003, 0.05]), but zero was a credible estimate for the remaining sessions: 0.02 [-0.004, 0.04] for session three, 0.1 [-0.003, 0.03] for session four, and 0.004 [-0.02, 0.03] for session five. This reduction was statistically significant [$F(4,32) = 4.17$, $p = .008$, $\eta_p^2 = .34$]. This pattern matches the standard RT analysis. Thus, the reduction of n–2 repetition cost with practice is independent of the overall speed of responding. It should also be noted that the reduction of n–2 repetition cost with practice also decreases when log(RT) is analysed, another common method for controlling for speed of responding. The sequence-by-session interaction for log(RT) was significant [$F(4,32) = 4.00$, $p = .01$, $\eta_p^2 = .33$].

3.2.2. RT Distribution Analysis. Given the wealth of trials per participant, we also took the opportunity to analyse whole response time distributions. To accomplish this, we fitted a mathematical function to the RT distribution for all participants for all sessions and sequence conditions. Specifically, we estimated ex-Gaussian parameters for each cell of the experimental design for each participant. The ex-Gaussian distribution—a convolution of a normal distribution and an exponential distribution—is often used to model RT distributions (Balota & Yap, 2011), and returns three parameters which describe the shape of the RT distribution: *mu*, which represents the mean of the Gaussian component; *sigma*, which represents the standard deviation of the Gaussian component; and *tau*, which reflects the rate of the exponential component (i.e. the tail end of the distribution).

Although we have no clear theoretical reason to expect a certain pattern in this analysis, Grange and Houghton (2011) observed that—at least in some data sets—the n–2 repetition cost increases throughout the RT distribution. Thus, if this pattern were to be present in the current data set, it would manifest as an effect of n–2 repetition on the tau parameter, which reflects the tail end of the RT distribution. Presentation of RT-distribution analysis also constrains model development (Balota & Yap, 2011), as any successful model must not only explain performance at the mean level, but also at the more-fine-grained distributional level. This extra requirement allows for discrimination of competing models in circumstances where mean performance is explained equally well.

Parameter estimation was conducted using the 'timefit' function of the 'retimes' package (Massidda, 2013) in **R** (R Core Team, 2013), which utilises a maximum likelihood method for estimation using bootstrap resampling with 1,000 iterations. The RT distribution data can be seen in the left column of Figure 4.

3.2.2.1. Mu Parameter. For this parameter there was no main effect of sequence, with no observable difference between ABA and CBA sequences (-0.16ms [-1.90, 1.58]) [$F(1,8) = 0.04$, $p = .84$, $\eta_p^2 = .00$]. There was also no clear modulation of this parameter with experimental session [$F(4,32) = 1.86$, $p = .14$, $\eta_p^2 = .19$]. There was also no difference
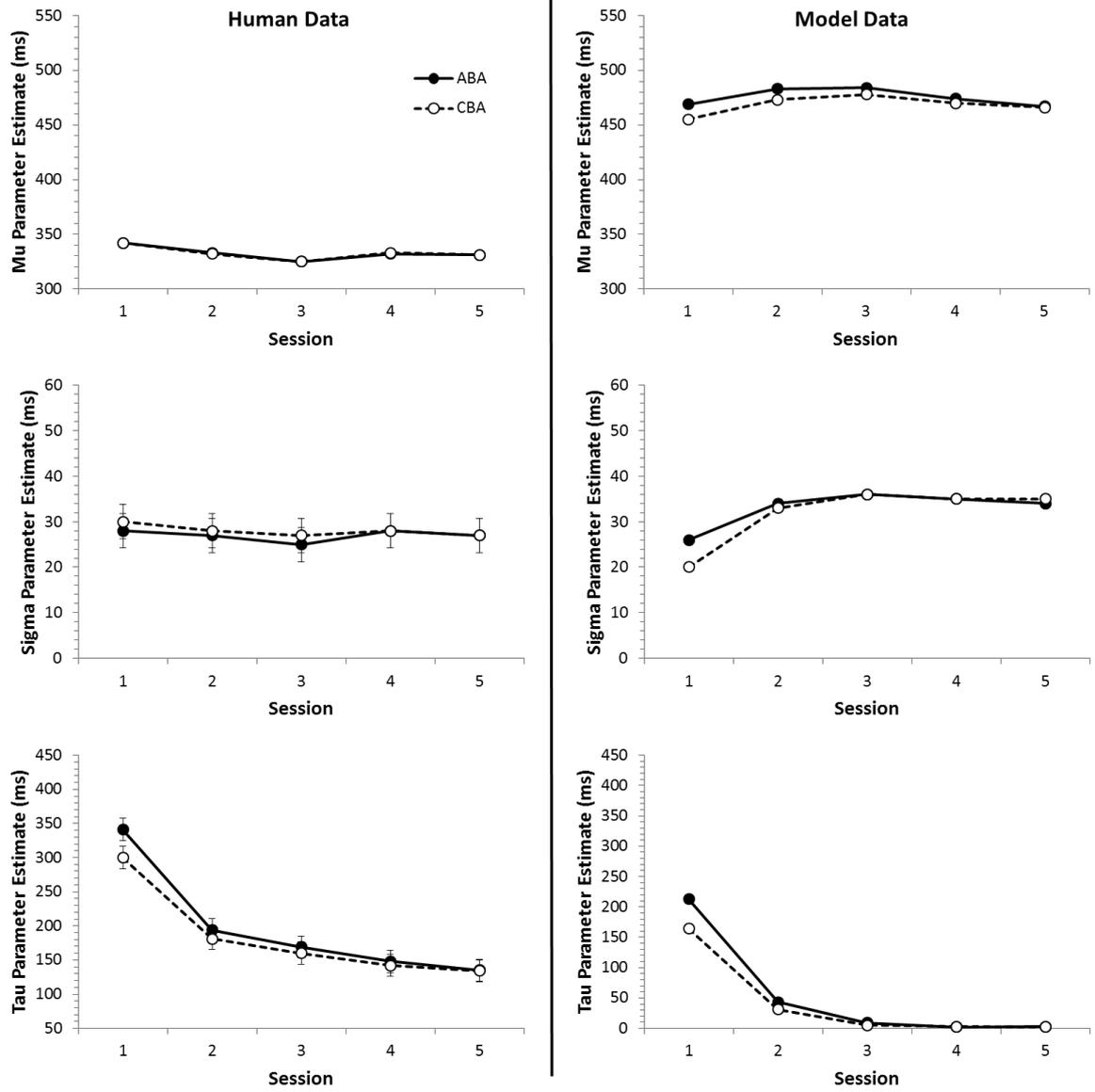
Figure 4

between the n–2 repetition costs in this parameter with experimental session [$F(4,32) =$ 0.4, $p = .99$, $\eta_p^2 = .00$]: -0.19ms [-9.03, 8.65] for session one; 0.59ms [-4.07, 5.26] for session two; 0.11ms [-4.47, 4.68] for session three; -0.80ms [-5.25, 3.64] for session four; and -0.50ms [-5.82, 4.81] for session five.

3.2.2.2. Sigma Parameter. For this parameter there was no main effect of sequence, with no observable difference between ABA and CBA sequences (-1.04ms [-3.21, 1.13]) [$F(1,8) = 1.23$, $p = .30$, $\eta_p^2 = .13$.]. There was also no clear modulation of this parameter with experimental session [$F(4,32) = 0.43$, $p = .79$, $\eta_p^2 = .05$.]. There was also no difference between the n–2 repetition costs in this parameter with experimental session [$F(4,32) = 0.36$, $p = .84$, $\eta_p^2 = .04$.]: -2.44ms [-8.31, 3.44] for session one; -1.05ms [-3.77, 1.67] for session two; -2.07ms [-7.65, 3.52] for session three; 0.22ms [-4.38, 4.83] for session four; and 0.11ms [-4.08, 4.81] for session five.

3.2.2.3. Tau Parameter. For this parameter there was a main effect of sequence, [$F(1,8) = 8.52$, $p = .02$, $\eta_p^2 = .52$], with the estimate for ABA being 14ms [3, 25] slower than for the CBA estimate. There was also a clear effect of session [$F(1,8) = 18.03, p < .001$, $\eta_p^2 = .69$]. Parameter estimates reduced by 133ms [69, 197] between sessions 1–2, 23ms [-10, 56] between sessions 2–3, 19ms [-5, 44] between sessions 3–4, and 11ms [-7, 28] between sessions 4–5. There was also a clear reduction of the n–2 repetition cost in this parameter with session [$F(4,32) = 4.93$, $p = .003$, $\eta_p^2 = .38$]. 41ms [7, 75] for session one; 12ms [-2, 27] for session two; 10ms [-2, 22] for session three; 6ms [-2, 14] for session four; and 1ms [-10, 12] for session five. It is interesting to note the parallel between the mean RT n–2 repetition cost and the estimates of the tau parameter (see left side of Figure 2 and the lower-left plot in Figure 4).

3.3. Individual Differences

Although we were primarily interested in the average n–2 repetition cost with extended practice, our data also afforded a closer examination of individual differences in the n–2 repetition cost (and its reduction with practice). Individual subject plots of RTs for ABA and CBA sequences for each experimental session can be seen in Figure 5, and individual n–2 repetition cost per 122-trial block can be seen in Figure 6.

Subjects 4, 5, 7, 8, and 10 showed a clear reduction of n–2 repetition cost with practice, whereas no such pattern was clear for the other subjects; subjects 2, 3, and 6 show no clear n–2 repetition cost pattern. (Subject 1 does show a reduction, but the 95% CI includes zero at early stages of practice.) This inter-individual difference in whether participants exhibit n–2 repetition cost does not seem to be related to the overall speed of responding for each participant, with the exception perhaps of subject 3 (see Figure 5). Subject 3 is striking due to the very low variance of n–2 repetition cost across all five sessions; this particular subject's mean RT was also very rapid, with incredibly little variance. It is not clear what is driving these individual differences, but it is evident that not all participants exhibit evidence of inhibition in set switching. Even those subjects who do exhibit n–2 repetition costs do not do so consistently; even among subjects 4, 5, 7, 8, and 10, negative n–2 repetition costs (i.e. benefits) are common in some sub-blocks.
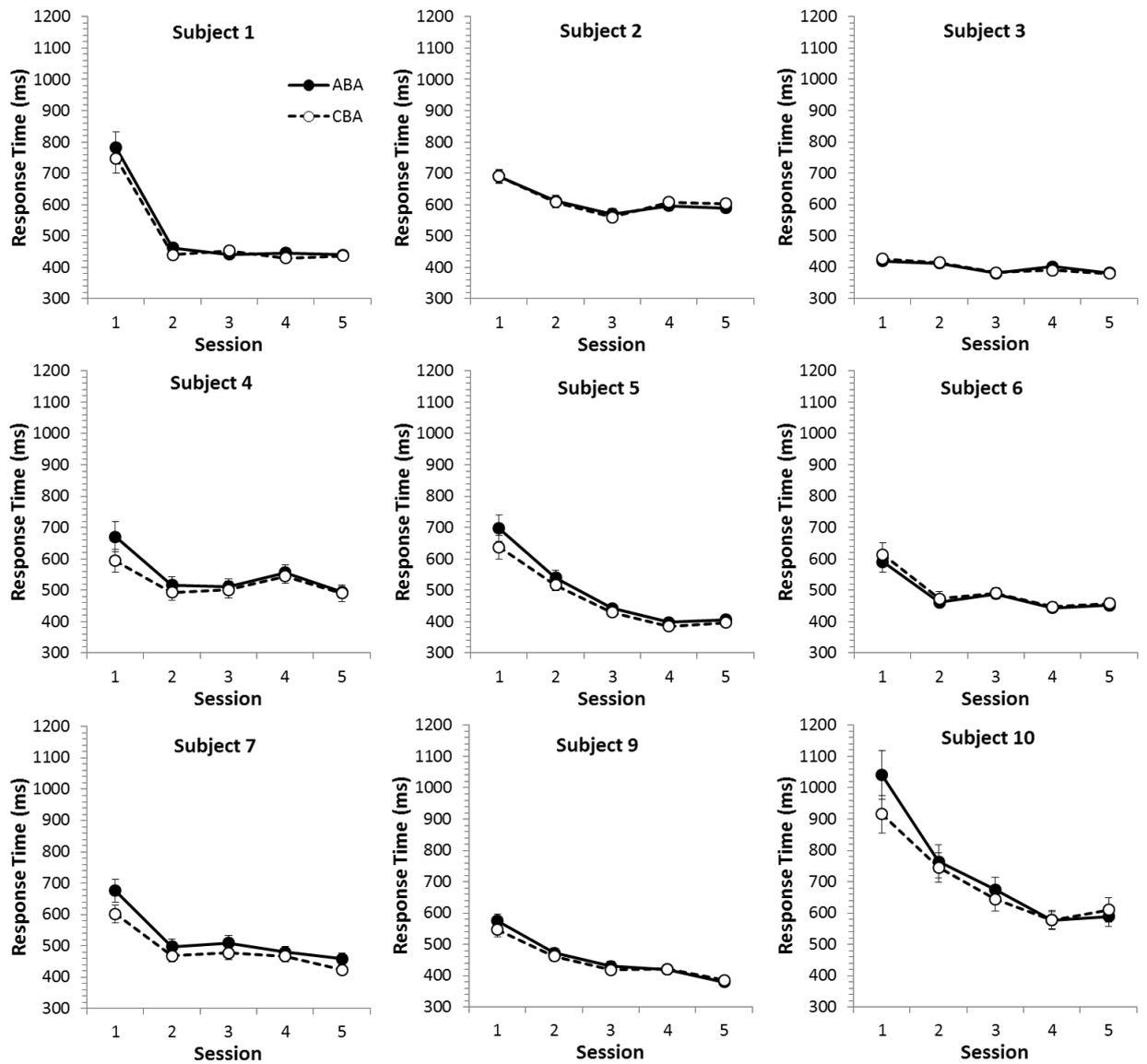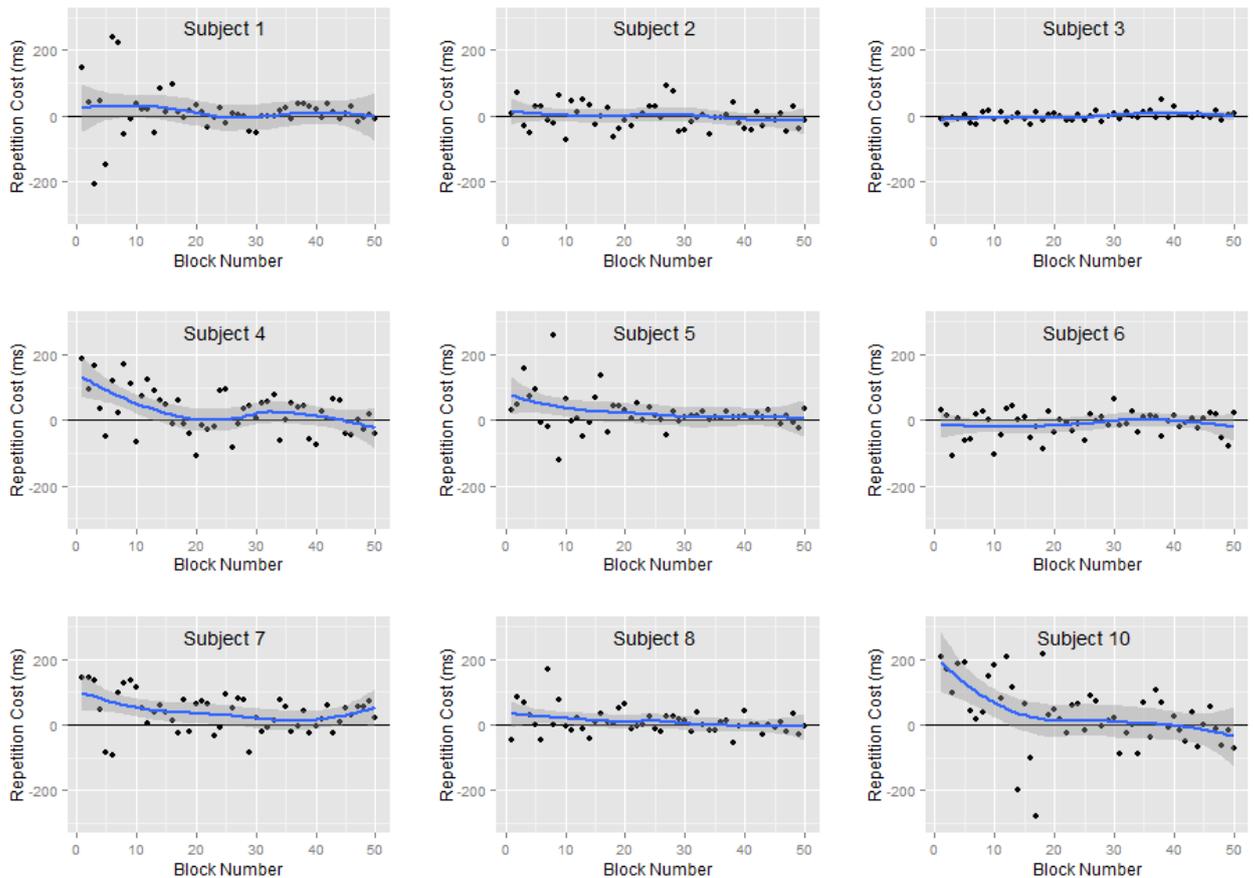
Figure 5

Figure 6

4. General Discussion

In this paper, we were interested in whether inhibition in set switching—as measured by the n–2 repetition cost—is modulated by the degree of practice participants have with the task at hand. We exposed participants to five experimental sessions of 1,222 set switching trials, and observed clear reduction of the n–2 repetition cost, being altogether absent from the final block. This is the first line of evidence suggesting that practice reduces observable inhibition in set switching. Although not the primary aim of our investigation, RT distribution analysis suggested that this reduction was generally caused by a reduction of the tau parameter of an ex-Gaussian fit, which reflects the tail end of the RT distribution (Grange & Houghton, 2011). We also took the opportunity to report individual differences in n–2 repetition cost and their reduction with practice. Not all participants exhibit n–2 repetition cost. It remains an interesting question how—if inhibition is necessary for task switching—these participants are able to switch tasks; we return to this discussion in a later section.

In this General Discussion, we consider these results in reference to the two theoretical derivations outlined in the introduction, before discussing how aspects of *both* accounts are needed to fully account for the data. Specifically, the model of Grange et al. (2013) is

extended here to include increasing associative strength between cues and their associated targets in declarative memory as practice progresses; this provides a formalisation of the cue–target translation hypothesis of Houghton et al. (2009): the increasing cue–target association strength speeds the retrieval of inhibited chunks from memory and increases the accuracy of these retrievals, thus reducing conflict present in WM (cf., Houghton et al., 2009).

4.1. Cue–Target Translation Automisation

In the introduction, we outlined why a reduction of the n–2 repetition cost might be expected from the cue–target translation hypothesis of Houghton et al. (2009): with practice, cue–target translation processes become automised (Logan, 1988), and thus less conflict is apparent in WM during switching which reduces the need for inhibition. Although the present data set cannot speak directly to the question of whether cue–target translation processes *were* automised, this process is likely the only one in each experimental trial that can directly benefit from practice (we discuss this detail in a later section). In the terms of Logan (1988), initial performance of cue–target translation is slow, because the participant has no pre-experimental association between the cue and the target, and thus performance must rely on a slow algorithmic route; increased practice with associating a square cue with a shaded target (for example) increases the instances of the cue–target associations stored in long term memory, which speeds performance because long term memory retrieval of stored instances is assumed to be a faster process than algorithmic performance. At performance, these processes race against each other, with speed of responding being determined by whichever process wins the race; the more instances that are stored increases the probability that the fast retrieval process wins.

One possibility is that less inhibition is required when the system starts to benefit from automatic retrieval of instances of cue–target associations from long term memory, as less conflict occurs in WM during cue–target translation. This is a natural extension to our previous work (Grange & Houghton, 2010b; Houghton et al., 2009) which has demonstrated that n–2 repetition cost in set switching is reduced when cue–target translation processes are facilitated.

4.2. Grange et al.'s (2013) Model Prediction

A reduction of n–2 repetition cost with extended practice was also predicted by a computational model of inhibition (Grange et al., 2013). In this model, recently retrieved task-related chunks in memory are inhibited; this inhibition renders these chunks temporarily less accessible, making their retrieval slower and more error-prone. As practice proceeds, the inhibition (see Equations 2 & 3) has less effect as the base-level activation of the chunks in memory gradually increases with practice.

However, the observed reduction was larger than predicted (Figure 1), with regard to both general RT and the n–2 repetition cost. Recall that the prediction was only based on the base-level learning component of the activation equation. Exploring the space of possible parameter values (e.g., memory decay) did not result in considerably better predictions. We therefore inferred that other learning mechanisms must occur in addition to base-level learning to account for the difference between prediction and observation. Thus, this partial

failure of the model to predict the magnitude of the practice effect was informative in that it suggested that something was missing in the original model.

In the next sections, we describe extensions to the Grange et al. (2013) model of inhibition in set switching, and describe fits to the practice data presented here.

4.3. Extending Grange et al.'s (2013) Model

There are several components contributing to successful human performance in this experiment which might be subject to practice effects, and hence be a candidate to include in the model to explain the observed reduction of n–2 repetition cost. However, it is important to note that in order to account for the reduction of n–2 repetition cost with practice, the task-set component (or process) becoming facilitated must have a greater effect on n–2 repetitions than on n–2 switches; that is, if any hypothetical process that becomes facilitated with practice affects n–2 repetitions and n–2 switches equally, the net effect would be no reduction of the n–2 repetition cost with practice. This consideration constrains the locus of the observed reduction. For example, the visual search component of the task might become facilitated (see e,.g., Sireteanu & Rettenbach, 1995), to the extent that searching for task-relevant properties of the multi-target display might become facilitated; as a consequence, orienting to the target will become faster with practice. However, such facilitation would benefit ABA and CBA sequences equally, and thus would not lead to a reduction of n–2 repetition cost.

4.3.1. Integrating Grange et al.'s (2013) model & Cue–Target Translation. One aspect that can explain the observed reduction of n–2 repetition cost with practice that is not captured by the current model is facilitated associative strength between cues and the targets they are paired with. In the original model, the strength of association between cues and targets was set and remained unchanged. The strength of association between a cue and the associated target determines the amount of activation that spreads from cue to target. If a cue and a target are strongly associated, the target will receive a high amount of activation when its associated cue is presented, which results in faster and more accurate retrieval. Thus, with greater associative strength, an inhibited target chunk can be retrieved from memory faster when its associated cue is presented, leading to reduced n–2 repetition cost.

Importantly, inclusion of such a process in the model of Grange et al. (2013) would provide a formalisation of the cue–target translation hypothesis proposed by Houghton et al. (2009). In the spirit of theoretical integration, we included such a mechanism in the model of Grange et al. (2013). Spreading activation in ACT-R is governed by the following equation:

$$S_i = \sum_k \sum_j W_{kj} S_{ji}. \tag{5}$$

S_i is the activation that spreads to chunk i. The elements k being summed over are all of the buffers in the model. The elements j being summed over are the chunks which are in the slots of the chunk in buffer k (these are referred to as the sources of activation). W_{kj} is the amount of activation from source j in buffer k. It is the source activation of buffer k divided by the number of sources j in that buffer. S_{ji} is the strength of association from

source j to chunk i. For our purpose here, there is only one source (the cue) in one buffer (goal) and S_{ji} is the strength of association between the cue and the memory representation of the target.

Total activation A of chunk i is now

$$A_i = \left(ln \sum_{j=1}^{n} t_j^{-d} - \gamma \right) + S_i. \tag{6}$$

The current version of ACT-R (i.e., ACT-R 6[6]) does not support learning of association strengths from practice. A previous version—ACT-R 4—had such an associative learning mechanism; many in the modelling community would agree that an associative learning mechanism is empirically justified, though its computational implementation is non-trivial. Efforts to develop an associative learning mechanism are currently underway in the ACT-R modeling community (Thomson & Lebiere, 2013). For demonstrative purposes, here we set the associative strengths (S_{ji} in the equation above) at values that increase with session (i.e., practice). This was necessary to fit the magnitude of the n–2 repetition cost reduction observed in the empirical data, but it was not sufficient to also fit the magnitude of the overall reduction in response time across sessions.

4.3.2. Decreasing Retrieval-Noise with Practice. Another aspect that came out of the empirical study that informed our modeling was the observation that variability in response time decreased with practice: standard error of the mean for sessions 1 to 5 was 51ms, 35ms, 28ms, 27ms, and 28ms, respectively. Based on this result, we set the activation noise in the model at values that decreased with session. Activation noise causes variability in activation, which in turn determines variability in response time. When the added decrease in activation noise was coupled with the existing increase in base-level activation with practice, the result was a steeper learning curve; that is, a larger magnitude of the overall RT reduction, as observed in the empirical data.

4.4. Model Fit Results & Discussion

The model fit to the mean RT as a function of task sequence and practice is shown in the right panel of Figure 2; the parameters used to fit the model can be seen in Table 2.[7] As can be seen, the model captured all of the main trends in the data. Although the model was only explicitly fit to the session data in Figure 2, examination of the dynamics of the model's predicted n–2 repetition cost as a function of each 122-trial block across the experiment showed that it reproduced the pattern in the human data very well (see lower panel of Figure 3.)

4.4.1. On Individual Differences. The empirical study also revealed important individual differences in n–2 repetition cost, and its reduction with practice (Figure 6). As the n–2 repetition cost is believed to be an important measure of cognitive inhibition (Koch et al., 2010), the n–2 repetition cost has started to garner interest in the literature examining individual differences in inhibitory control. For example, Whitmer and Banich (2007) showed that participants with higher-levels of depressive rumination had smaller

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[6]http://act-r.psy.cmu.edu/software/

[7]We refer the interested reader to Grange et al. (2013) for full specification of the model. ACT-R source code for the current model can be supplied as supplementary material.

Table 2

The best fitting parameter values and fit statistics for the inhibition model (see General Discussion). RMSD = root mean square deviation. Note that the five values for the activation noise and the strength of association parameters reflect the values for sessions 1–5 respectively.

Parameter	Description	Default Value	Fitted Value (s)
:lf	Latency factor	1.0	0.7
:bll	Base level learning (decay [d] in Equations 1 & 2)	nil	0.5
:ans	Activation noise	nil	0.5, 0.35, 0.25, 0.15, 0.05
:rt	Retrieval threshold	0	-2.6
sji	Strength of association	1	0.05, 0.25, 0.60, 1.20, 2.00
:inhibition-decay	Base level inhibition decay (ds in Equation 2)	1.0	1.1
:inhibition-scale	Base level inhibition scale (ts in Equation 2)	5	From 0 to 14

$R^2 = 0.992$
RMSD = 6.93ms

(sometimes reversed) n–2 repetition costs. Thus, the n–2 repetition cost is a promising marker with which to explore individual differences in inhibitory control.

In our study, we have shown a wide range of individual differences in the n–2 repetition cost in a healthy sample. This suggests that there is much individual-difference in the n–2 repetition cost. Interestingly, some subjects (e.g., Subjects 3 and 6 in Figure 6) showed no evidence of n–2 repetition cost at all. Assuming that at least part of this inter-individual variability is of potential theoretical relevance to the understanding of inhibition in task switching, we wanted to explore this in the model simulations.

We addressed individual differences in n–2 repetition cost by varying one of the inhibition parameters: the inhibition scaling parameter (T_s). In the simulations we varied this parameter between 0 and 14 in increments of 1. Figure 7 shows a random selection of model "participants" and their reduction of n–2 repetition cost with practice. As is clear, the model exhibits both intra-individual variability (i.e., stochasticity in memory retrievals) and inter-individual variability (variation in n–2 repetition costs).

These simulations show that the inter-individual variation in n–2 repetition cost is well-replicated by the model by selectively varying the degree of inhibitory strength in the model; this adds to the general agreement in the literature that the n–2 repetition cost is a valid marker of cognitive inhibition during set switching (but see Grange et al., 2013, for some important constraints on this issue). We note that individual differences in n–2 repetition cost could also be explained by variation of the inhibition decay parameter between subjects rather than inhibition itself; with constant inhibitory input, faster inhibition decay would lead to a smaller n–2 repetition cost than if inhibition decay was slower[8]. Future

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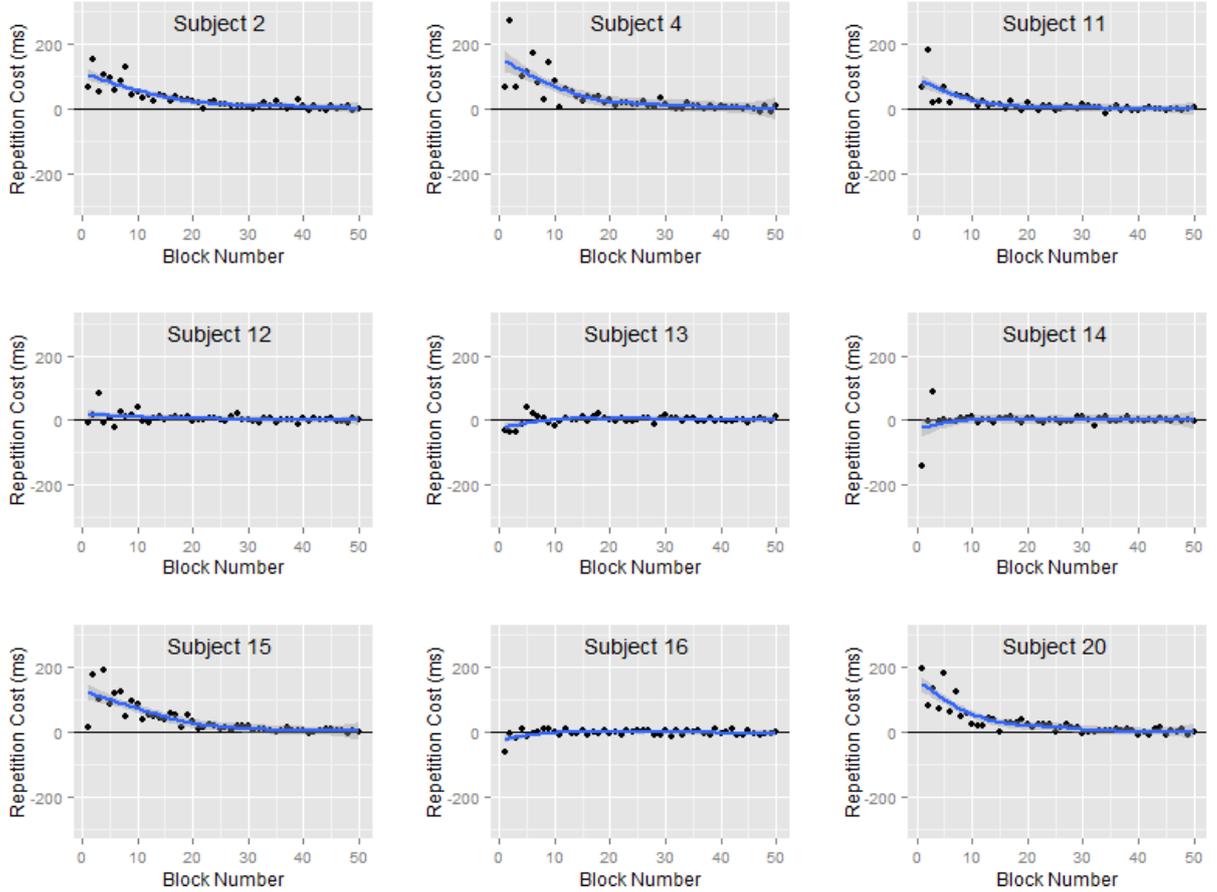[8]We thank Iriing Koch for this point.

Figure 7

empirical and theoretical work should attempt to decide between these accounts.

4.4.2. Response Time Distributions. In this section, we explored the ability of the model to account for the results of the response time distributional analyses (Figure 4), even though the model was not directly fit to these data (i.e., the model was fit to mean RT alone). We reasoned that if all the necessary mechanisms are included in the model, the distributional data should implicitly be accounted for. Thus, these data provide important information regarding the fit of the model to more-fine grained data. The model distributional analyses can be seen in the right panel of Figure 4.

First thing to notice is that there are differences in scale between the observed and simulated data: mu estimates are larger and tau estimates are smaller in the model than in the human data. These differences are caused by the lower variability in the model than in the human data. We deliberately chose to not reproduce the full range of variability in the human data to avoid a common problem in post-hoc modeling; that is, fitting the noise. Thus, we can ignore differences in scale and focus on qualitative differences between the distributional parameters. As can be seen in Figure 4, the model shows clear inhibition and practice effects on all three ex-Gaussian parameters (i.e. difference between ABA and CBA sequences at early sessions, with the difference attenuating with practice); in the human

data only the tau parameter shows significant inhibition and practice effects. This result is surprising and difficult to interpret at this moment. It could be that the model fails to explain why the n–2 repetition cost occurs preferentially at the tail of the RT distribution, or the human data is too noisy to show the significant effects on mu and sigma that are predicted by the model. Further research is needed to elucidate this dilemma.

4.4.3. Model Fit—Summary. In summary, the original model predicted the reduction of both n–2 repetition cost and overall RT with practice, but it underestimated the actual magnitudes of these effects. Two amendments were necessary to improve the model fit: increasing activation strengths and decreasing activation noises with practice. In so doing, we have been able to integrate the computational model of Grange et al. (2013) with the cue–target translation hypothesis of Houghton et al. (2009), providing an important link between different research programs.

4.5. Future Directions

4.5.1. Conflict-Triggered Inhibition. The above has shown that in order to reproduce the reduction of n–2 repetition cost with practice, we had to include the assumption of increasing cue–target association strength with practice and the increasing base-level activation with practice. Thus, although we outlined in the Introduction two seemingly separate theoretical reasons to predict a reduction of n–2 repetition cost with practice, we have had to use elements of both to fully account for the data.

Prima facie, it might appear that increasing cue–target association strength in the model reported here is not a faithful formalisation of the cue–target translation hypothesis of Houghton et al. (2009). Recall that their hypothesis was that aiding cue–target translation leads to a reduction of interference (or conflict) in working memory when a switch of attentional set is required. As a consequence of this reduced interference, less inhibition is required, leading to a reduced n–2 repetition cost. That is, in their hypothesis, inhibition is triggered by—and is directly proportional to—the degree of interference registered in the system. By contrast, inhibition in the model here is not triggered by interference. Although conflict-triggered inhibition is present in some computational models of selective attention (see e.g., Houghton & Tipper, 1994), a computational implementation of this is yet to be explored in the area of task switching, and remains an essential avenue for future research.

However, we see more similarities than differences between our account and that of Houghton et al. (2009). Although inhibition in the current model is not triggered by the degree of interference present, the amount of inhibition used *is* proportional to the amount of interference in the system. ACT-R models interference as the probability to retrieve the "wrong" chunk. This happens when the "right" chunk does not have enough activation relative to its competitors (either due to decay or inhibition). During early stages of practice, a required chunk's activation will be low due to low base-level learning; due to weaker associative strength between a cue and a target, presentation of the cue does not enhance the required chunk's activation as much during early stages of practice. With this reduced activation, the inhibitory subtraction (Equation 2) is large relative to total activation, and has greater effect on the chunk's dynamics. During early stages of practice, all chunks will have relatively low activation, and so interference can be considered high. With practice, however, a required chunk is relatively more active (due to higher base-level learning and increased associative strength), and so the inhibitory subtraction has less effect.

In addition, interference is reduced because the increased associative strength together with the increased base-level learning allows rapid activation of the target chunk over and above its competitors.

Taken together, the above shows how the model also suggests that inhibition is relative to the degree of conflict present, even though it is not triggered by the conflict (cf., Houghton et al., 2009). It also highlights that inhibition in the model in *absolute* terms is constant and unchanging as practice progresses; as the activation of chunks begins to grow (due to increasing base-level learning and increased associative strength when a cue is presented), inhibition in *relative* terms decreases as practice progresses.

It is essential to compare statistically the fit of our model in comparison to a computational implementation of conflict-driven inhibition to see which provides a better account— in terms of fit and parsimony—of n–2 repetition cost data. This remains a pressing issue to explore in future work. This is pressing because data exists besides that of Houghton and colleagues (2009) suggesting n–2 repetition costs are generated by conflict-driven inhibition (Gade & Koch, 2005; Scheil & Kleinsorge, 2014). In addition, a limitation of our data is that it is not able to decisively rule out conflict-driven inhibition, as practice is exerting a uniform influence on all aspects of the trial equally[9], so it is difficult to ascertain with certainty which aspect of trial performance is becoming facilitated (and hence, whether it is related to conflict-reduction or not). Future work should address this limitation by designing experiments capable of arbitrating between conflict and no-conflict accounts of the n–2 repetition cost, and to compare statistically fits of models that implement conflict-driven deployment of inhibition and those that do not.

4.5.1.1. Cue–target transparency manipulations. However, Houghton and colleagues (Grange & Houghton, 2010a; Houghton et al., 2009) claim to have provided empirical evidence for conflict-driven inhibition in set switching by showing the n–2 repetition cost reduces with increased cue–target transparency. They suggest that less-transparent cue–target relationships (e.g., a square cue being paired with a shaded target) require a process of cue–target translation in working memory, which can be a source of interference when the relevant target switches on the next trial (thus triggering inhibition, and a large n–2 repetition cost). More-transparent cue–target relationships (such as a shaded rectangle cuing the shaded target) require less/no cue—target translation, and thus generates no interference when switching attentional set (and no n–2 repetition cost). At first blush, this pattern of data is difficult to reconcile with the model presented here, where inhibition is not related to the degree of interference.

We conjecture that these findings can be explained by our model, as highly-transparent cue–target relationships are likely to have strong associative links between the cue and target chunks in memory. Thus, if we assume inhibition is equal in both cuing conditions, the stronger associative link between cue and target for highly-transparent cue–target relationships will lead to faster activation of inhibited chunks in memory, leading to reduced n–2 repetition costs as is observed. From this perspective, cue–target transparency does not influence the amount of inhibition used, but rather the speed with which this inhibition can be overcome. This conjecture makes the interesting prediction that inhibition is present even for maximally-transparent cue–target pairings, even though n–2 repetition costs are

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[9]We are grateful to an anonymous reviewer for highlighting this issue.

never reported for them (see Houghton et al., 2009, Experiment 1). We are exploring this prediction in ongoing work.

4.5.2. Set Switching Versus Task Switching. In this experiment presented to humans and to the model, we used a somewhat atypical version of a switching paradigm in that it required switching attentional set rather than task switching, per se. This paradigm is very similar to that used by Mayr and Keele (2000) who first reported the n–2 repetition cost. This might limit the conclusions we have reached in the current paper to similar set switching designs.

It should be noted, though, that many (if not all) task switching effects have been reported using this set switching paradigm: n–2 repetition costs (Grange & Houghton, 2009, 2010b; Houghton et al., 2009); cue-switch costs that decrease with increased cue–stimulus interval (Grange & Houghton, 2010a); "set-switch costs", that reduce with increased cue–stimulus interval (Grange & Houghton, 2010a); restart costs and within-run slowing (Grange, 2010). This perhaps should not be surprising, as switching attentional-set is likely a core aspect of task switching (Logan & Gordon, 2001). Thus, although the findings reported in the current paper come from a set switching paradigm, this paradigm reproduces many task switching effects. It remains an important avenue for future work to explore how practice affects performance in more traditional, task switching, designs, and whether our model is generalisable to these data.

4.6. Conclusion

We have provided empirical evidence for a reduction in n–2 repetition cost in set switching, and have outlined plausible theoretical explanations for this reduction, supported by computational simulation. This work has shown that inhibition—as measured by the n–2 repetition cost—has its greatest effect on performance when the tasks being performed are relatively novel. With practice, we suggest that the cognitive system benefits from increasing activation of task-related elements in memory, as well as increasing associative strength between cue–target pairings. The net effect is a reduction of the n–2 repetition cost with practice.

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