Now you see me, now you don't: Adapting practice through target exclusion negatively impacts motor learning

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Abstract

How to optimize practice through scheduling of different task components or skills is a question that has received a lot of attention in motor learning research. Consistently, schedules with high variability in the order that skills are practiced elicit better learning outcomes than schedules with low variability. Another idea is that learners should seek to reduce the uncertainty of a practice outcome, by avoiding well-learned, low error components in acquisition. To test this idea, we used a target exclusion method to prevent learners from returning to task components with low error and studied how individuals given choice over practice choose to allocate time to components of varying difficulty. We compared exclusion methods in a random-schedule group, a self-control group and in a yoked, matched-schedule control (6 groups total) in a multi-target adaptation paradigm. To manipulate uncertainty, we excluded targets from practice once participants attained a criterion error score (mean $<5^{o}$) from the last 5 trials to the same target. Contrary to our predictions, groups that practiced without target exclusion were more accurate in retention compared to exclusion groups; irrespective of practice schedule. Self-control groups adopted uncertainty-based practice, spending more time at difficult targets and less time at easier targets. However, there were no group differences in error, based on schedule-type (random, self-control and yoked). In conclusion, target exclusion was not an effective method for learning and did not support the efficacy of uncertainty-based practice for learning novel skills. There were benefits from keeping easier/low error skills in practice for later retention. This did not appear to be related to the increased switching between skills, but could be related to increased task engagement and more optimal challenge associated with practice on a range of target difficulties, rather than the most difficult.

Keywords: Contextual interference, challenge-point, self-determined practice, adaptive practice.

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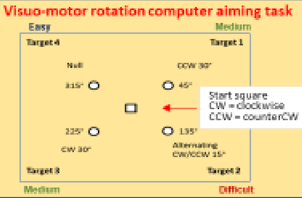
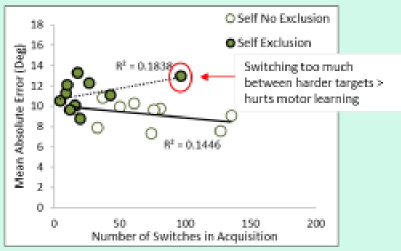
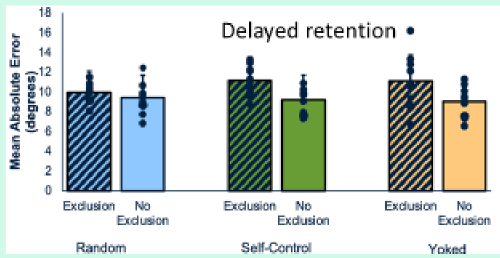
2X3 between-design: Targets excluded when criterion error consistently attained

	Random Target Order	Self Controlled Order	Yoked (to Self gps)
Target Exclusion	Exclusion-Random	Exclusion-Self	Exclusion-Yoked
No Target Exclusion	No Exclusion-Random	No Exclusion-Self	No Exclusion-Yoked
	n = 20	n = 20	n = 20







Conclusions: Allowing learners to return to relatively easy task components is good for learning and self-learners choose to do this. Optimal challenge can be gained through a mixture of low, medium and high difficulty practice components

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1. Introduction

In motor learning, there is considerable research showing that schedules of practice that are best for learning are those that encourage high variability in the order in which skills are practised (for a recent review see Wright & Kim, 2020). However, it is becoming increasingly recognized that the practice schedule which is most effective for learning is the one that considers both the learners' engagement in learning the task and the difficulty of the task itself (eg., Guadagnoli & Lee, 2004; Wulf & Lewthwaite, 2016). One method for adapting practice to task difficulty is to prevent return to task components which are easy, limiting practice to more difficult components later in practice. In this experiment, we study whether an exclusion-based method of adapting practice is beneficial for motor learning and second, whether individuals given choice over practice adopt such a method in scheduling their own practice.

There is strong evidence to support the use of practice schedules that tend to yield relatively errorful performance during practice. Practising different skills or tasks in a random versus repetitive order benefits later retention of motor skills, even though there may be temporary difficulties in practice. This has been termed the contextual interference (CI) effect, due to the delayed benefit of interference experienced during practice (Magill & Hall, 1990; Shea & Morgan, 1979). Because of negative self-judgments of learning resulting from poor performance in acquisition with a random schedule (e.g., Simon & Bjork, 2001), negative affect associated with poor competency judgements (Wulf & Lewthwaite, 2016), and poor efficacy of high interference schedules when task difficulty is high (e.g., Guadagnoli et al., 1999), other ways of scheduling practice to optimize learning have been considered. This includes adapting practice based on an individuals' performance as well as allowing learners to schedule their own practice.

An example of a performer adapted practice is the win-shift/lose-stay strategy. This practice is characterized by task switching that is contingent on the learner reaching a criterion level of accuracy before moving to a new task (Porter et al., 2019; Simon et al., 2008). In the study by Simon and colleagues, learners practised three different sequences, but were forced to switch when errors were low (within a criterion band for one or two trials). Individuals were allowed to switch back to these previously “mastered” sequences and they had a forced number of trials to complete at each sequence. In comparison to a non-adaptive random practice, the win-shift strategy did not, however, lead to better retention. In a similar win-shift paradigm involving a basketball set shot, participants in the learner-adapted group switched shooting locations after successful trials (Porter et al., 2019). Compared to baseline, this win-shift adapted group was the only group to show improved performance on a transfer task, but not in immediate or delayed retention. Moreover, the win-shift group did not differ from blocked and random control groups in retention. One of the issues with this method may be that learners continually switched back to easier components. Another concern is that individuals did not have any control in determining their schedule of practice.

Allowing learners control over how they organize their practice of multiple skills has received mixed support in terms of being an effective method of practice (Ste-Marie et al., 2020). For example, Wu and Magill (2011) showed retention advantages in a keypress sequencing task for self-control groups in comparison to yoked groups, which followed the same switching schedule as a self-control partner. As the authors and others have argued, self-controlled practice allows learners to shape their practice to satisfy their performance needs or preferences, more than a fixed schedule (Chiviacowsky & Wulf, 2002, 2007). However, evidence that self-controlled practice is better than recommended fixed practice schedules such as random practice, is lacking. Titzer and colleagues (1993) showed that learning a timed barrier knockdown task benefited from a random versus blocked schedule, but a self-control group only outperformed the blocked group in retention.

In a study examining self-control of practice in the context of varied task difficulty, having control over practice order did not lead to improved retention compared to various fixed schedules (blocked and random; Keetch & Lee, 2007). However, self-control groups continued to improve in a 24-hr retention test, which was not the case for random, blocked, or yoked-schedule groups. The authors proposed that having control over practice order encourages performance-contingent strategies that best optimize task switching. This conclusion was supported by data showing that self-control participants switched after trials which were relatively more accurate in comparison to relatively more errorful. However, individuals also returned to these easier tasks. In much of the self-control of practice literature, individuals have been forced to practise a set number of trials of each task or target, rather than being allowed to choose how many trials of each type to practice. One notable exception to this constraint was a sequence learning task by Wu and Magill (2011). Individuals were allowed to practise each sequence as many times as they wanted, resulting in differences in the amount of practice on each task. However, the tasks did not differ in difficulty and no data were reported showing the frequency of revisiting low error sequences.

Self-control learners have also been shown to be suboptimal in their selection strategy in addition to performing less accurately than participants in random schedule groups (Huang et al., 2008). In research using a force-field adaptation task, random-scheduled learners performed better on same day test-trials than individuals allowed to choose what to practice, although delayed retention was not tested. Borrowing a model deemed optimal in machine learning, that of uncertainty-based selection (Cohn et al., 1996), Huang and colleagues argued that optimal learning occurs when the goal is to minimize a learner's uncertainty, such that learners should avoid well-learned task components in order to allocate more time and effort to task components with high uncertainty.

There are commonalities between the uncertainty-based selection strategy and the challenge-point framework conceptualized by Guadagnoli and Lee (2004). According to this framework, increasing task difficulty relative to the competency/skill of the learner increases the available information for learning and hence creates uncertainty. Learning does not occur in the absence of (new) information and deteriorates in the presence of too much information. An optimal challenge-point is attained when enough information is available to cognitively engage the learner, but not enough to overburden the individual and stifle learning. Therefore, a certain degree of uncertainty acts as a signal to the individual indicating that learning needs to occur and the learner should continue to practise the skill.

The purpose of the current study was to evaluate the effectiveness of an uncertainty-based selection strategy for motor learning; either one enforced through task exclusion or chosen by participants based on task difficulty. Like Huang and colleagues (2008), we used an adaptation paradigm to manipulate target difficulty during a reaching task to different targets. Target difficulty was manipulated by imposing a unique visual rotation between computer cursor feedback representing the participant's movement trajectory and the actual movement trajectory of the participant's unseen hand. We included a retention test to study learning, not just adaptive performance. Participants were either given a random schedule of practice or self-selected their own schedule, with or without target exclusion based on consistent low error. As a secondary aim, self-control participants were matched to yoked-schedule controls, to evaluate potential benefits associated with self-control of practice.

Our main interest was in determining whether there were learning benefits associated with the exclusion of well-performed task components during acquisition. If such a method is effective for learning, we should see better performance on a delayed retention test for target exclusion groups relative to no-target exclusion groups. We did not expect an interaction with schedule-type (Random, Self or Yoked), unless removal of choice after having choice for self-control groups, is negatively perceived and impacts learning (Wulf & Lewthwaite, 2016). In terms of main effects associated with schedule-type, if choice and practising in a performance dependent manner facilitates learning, then self-scheduled groups should have lower error on retention tests than yoked groups. We were unsure whether random practice would be better for learning than self-controlled practice, given that the evidence is relatively mixed.

A secondary interest was in determining what schedules of practice individuals choose when faced with targets of varying difficulty and whether they adopt a strategy that minimizes uncertainty through practise of more difficult targets and the avoidance of easier ones. Based on past data, we expected participants in the self-control groups to switch between targets a relatively low amount compared to random practice participants and that switching choice would be related to error, with more switching from easier/low error targets than difficult/high error targets. If self-control groups choose a practice schedule that minimizes uncertainty, then we would expect them to spend more time on the most difficult target and the least amount of time on the easiest target.

2.1. Methods

2.2. Participants

Sixty university students between the ages of 18 and 24 years participated after responding to an advert (they received ~$15 remuneration). All participants were self-reported right-handed and naïve to the purpose of the experiment. Participants were randomly assigned to one of six groups; with the constraint that yoked participants were assigned last: Self-control, with or without target exclusion, Random-order with or without target exclusion, and two Yoked groups, whose practice schedule was matched to the two Self-control groups (Exclusion and No-exclusion). All participants gave written informed consent and the study was conducted in accordance with the ethical guidelines set by the University of British Columbia. Due to our primary interest in main effects associated with target exclusion, the experiment was powered with n = 20/group to detect such effects (based on 2 X 2 factorial between-subject designs, as detailed in data analysis). Although target exclusion has not been used in previous work and Huang et al. (2008) used a repeated measures design to compare learners that had self-control or experienced a random practice schedule during a one-day protocol, our effect size estimate was based on group differences observed between self and yoked groups in delayed transfer testing in Wu and Magill (2011; n=15/group, Cohen's *d* values for 3 dependent measures ranged from = 1 - 2.71). Based on the lowest effect size, $\alpha = 0.05$, $\beta = 0.20$, we would need a minimum of n=17/group to detect between-group differences in retention.

2.3. Task and Apparatus

The experimental protocol and task stimuli were all programmed using a PC (Dell Inspiron 531, AMD Athlon™ 64x2, 5600+, 2.9GHz dual core processor; Windows Vista OS) and LabVIEW™ software (version 9.0, National Instruments). Participants were seated in front of a semi-silvered mirror, fixed 30 cm above a graphics' tablet (Calcomp Drawing Board III, 225 Hz, 200 lines/cm resolution). An upturned display monitor (ViewSonic E70f – CRT 17" monitor, 1280 X 1024 resolution, refresh rate: 66Hz) set up 30 cm above the mirror projected an image of the targets, starting square, and cursor trajectory onto the mirror. Participants controlled the cursor by moving a custom mouse on the graphics' tablet. Movement of the cursor corresponded with the spatial position of their right index finger (for a detailed description of apparatus, see Larssen et al., 2021). During a trial, a central starting square was first presented (0.5 cm inner length), surrounded by four radially arranged targets (0.25 cm inner diameter) positioned at a 10 cm radius. Targets were positioned at 45°, 135°, 225°, and 315° from the central square and individuals were required to practise moving the cursor from the centre starting position, through each of the four targets, as illustrated in Figure 1.

To ensure differences in target difficulty, we applied novel and different perturbations to three of the four targets (see Figure 1). The array of targets included an easy target with no perturbation (Target 4), two medium difficulty targets comprising a 30° clockwise (CW) rotation (Target 3) and a 30°

counter clockwise (CCW) rotation (Target 1), and a difficult to acquire target with an alternating CW and CCW 15° rotation (Target 2).

Vision of the participant's arm was occluded at all times by turning off the lights under the semi-silvered screen and darkening the room. Participants received terminal feedback of the (rotated) cursor trajectory immediately after their right index finger had exceeded the 10 cm radius between the central start position and the illuminated target (for ~1s duration). To prevent online correction of the reaching movement, fast, shooting type movements were encouraged and targets turned red on trials that were slower than 300 ms. Trials exceeding this criterion were not excluded from analyses, but these trials were ~5% or less of trials; range 5.5% (Self, Exclusion) to 2.7% (Self, No-Exclusion). Following each trial, participants moved the cursor back to the centre starting square. Vision of the cursor position was restored when individuals were within 5 cm of the start square and the next trial began once the cursor was within this square for 700 ms.

2.4. Design and Procedure

Participants in self-control groups were given control over the order of their practice, being able to choose what target to aim to on successive trials. In contrast, participants in the imposed, random-order practice group had their target practice schedule determined for them (a unique random schedule was provided to each participant). Additionally, participants were either subject to performance-dependent target exclusion or not, which was based on the attainment of a criterion error score (average of less than 5° error based on the last five trials to the same target). As such, targets that were well-learned (or consistently low in error) were removed from the task so they could not be selected (in the Self-Exclusion group) or did not re-appear (in the Random-Exclusion group). We based our exclusion criterion on existing literature where win-shift/lose-stay type strategies have been studied (e.g., Porter et al., 2019; Simon et al., 2008), as well as our own work with this adaptation task (e.g., Larssen et al., 2012;

Lim et al., 2014). In the former case, individuals are forced to switch when errors are low after only one or two consecutive trials, however, they are then allowed to return again to these targets. We determined that increased consistency (reflecting greater competency at a target component) would be needed if targets were to be excluded from practice. In the latter case, for these adaptation tasks where rotations are included, errors reduce quite quickly to ~5 degrees after ~25-50 trials of aiming to multiple targets with one rotation. Only small decreases are typically noted thereafter (e.g., Larssen et al., 2012; Lim et al., 2014). Two other imposed schedule groups followed the same practice schedule that was chosen by their self-controlled pair, resulting in yoked practice conditions to either the Self, Exclusion or No-Exclusion groups.

The experiment consisted of 3 phases: familiarization, adaptation, and delayed retention. Participants first practised in a normal visuomotor environment for 40 trials to become familiarized with the task and apparatus. The normal visuomotor environment did not perturb the feedback of any of the participants' movements, such that cursor feedback was veridical to their hand position. Participants were told to move as quickly and accurately as possible directing their index finger on the mouse to the target and informed that if a target turned red, their movement was too slow. Each target appeared one at a time in a pseudo-random fashion until participants reached to each target 10 times. After familiarization, the participants were informed that the next phase of the experiment would include 240 trials where the cursor would respond differently to their movements depending on the target. Self-control groups were informed that the targets instead of showing up one at a time, would show up all at once and they would have to decide the order and frequency of practice to each target. For the Random and Yoked groups with an imposed schedule, targets appeared one at a time. For the Random groups, target selection was truly random for each participant (computer generated), such that there were repeats to a target[1]. For the Yoked groups, each individual was matched to the practice schedule of an individual in the Self-control groups. Only the Random-No Exclusion group was constrained to make the same number of attempts to each target across the entire practice session. Due to our interest in the effects of target exclusion and self-controlled practice, no constraints were placed on number of target attempts for participants practising with the performance-dependent target exclusion criterion and/or self-control of their practice. Participants were reminded to move as quickly and accurately as possible. All participants were encouraged to engage in practice with the aim of performing well on the following day, which would consist of a retention test to measure how well they had learned to aim accurately to all four targets.

Retention testing happened the following day (~24 hours later). Participants were told at the start of retention testing that the conditions would be the same as those experienced the previous day where the targets had different cursor related feedback. The retention test consisted of 40 trials and targets appeared in a random order. After the retention test, participants were debriefed and compensated.

2.5. Data analysis

Initial data reduction was performed using the same custom LabView program used to run the experiment. Aiming errors were calculated by measuring the angle between the straight line connecting the origin (central starting square) and the target and the line connecting the origin and cursor feedback (based on index finger position) recorded at peak tangential velocity. All aiming errors were transformed to absolute values for group analysis. For all analyses we first focused on our primary research questions

[1] For all targets and for both random groups, the mean number of repeats to a single target ranged from 1.18 – 1.78 (SDs range .40 - 1.81). The one exception to this was for the Exclusion group, target 2 (the most difficult, alternating target), where the mean number of repeats was 7.92 (SD = 26.7). This was a consequence of repeated trials at this target at the end of practice when most other targets had been excluded.

concerning the effects of target exclusion and whether individuals chose to adopt an uncertainty-based practice when given the choice. To answer these questions, we conducted a fully factorial ANOVA: 2 Schedule-type (Self, Random) X 2 Exclusion (Exclusion, No-Exclusion). This factorial ANOVA allowed us to maximize power to detect main effects associated with practice control and exclusion (n=20/group for these analyses). Although of secondary interest, comparison of the Self and Yoked groups allowed us to make conclusions about practice benefits linked to performance and choice. As such, a secondary analysis was run involving a second fully factorial 2 Schedule-type (Self, Yoked) X 2 Exclusion between-participants ANOVA, this time comparing the Self-control to the Yoked groups. Again, this analysis maximized power to detect main effects of either schedule-type or exclusion-group, now controlling for the effects of practice schedule (with exclusion being performance dependent only for the self-group). Given the non-independence of groups across the two analyses, we were cautious in drawing strong conclusions from these secondary analyses, interpreting significant main effects at $p<.01$. We also conducted exploratory analyses based on accuracy for the 4 individual targets.

Retention data were of primary interest as magnitude of aiming errors after a 24-hr delay provided our measure of learning, so we present these data first. Acquisition was characterized by independent analyses of the absolute aiming errors and switching/target selection behaviours during practice. The error data was analyzed in the factorial ANOVAs as detailed above, with the addition of a 12 Block (20 trials/block) repeated measures (RM) factor along with Target (4 levels). Due to differential practice amounts at each target depending on group, a second analysis of error was conducted with practice divided into Early, Middle and Late third blocks.

To analyze process data regarding what and how practice choices were made, we first calculated percentage of trials to each target for the Random and Self-groups (note the Yoked groups were constrained to adopt the same switching schedule as the Self-groups) and compared these data in a factorial ANOVA with Target as a RM factor. We also calculated overall frequency of switching as a function of group and analyzed these data in a 2 Schedule-type (Self, Random) X 2 Exclusion X 4 Target ANOVA, with RM on the last factor. These latter analyses give an indication of the amount of contextual interference (CI) chosen by the Self groups in comparison to the high CI Random groups. Correlations between switching amounts and error in retention were also performed for the Self groups to alert as to individual differences in practice strategies and their relation to overall learning. Because participants had unequal trials to each target and hence the switching frequency as a function of target was related to the number of trials at each target, we also calculated proportion of trials where switching occurred as a function of target and performed similar ANOVA analyses focusing on target effects. Finally, we determined whether switching was dependent on relative error in practice, comparing absolute error on trials where a decision was made to repeat a target to trials where a decision was made to switch targets. A similar factorial ANOVA was used to run these analyses, with Trial-type (switch or repeat) included as an additional RM factor.

Violations to Sphericity were adjusted using Greenhouse Geisser adjustments to degrees of freedom. Tukey HSD procedures ($p<.05$) were used to follow up significant effects involving more than two means.

3. Results

3.1. Retention

Absolute error data in retention is shown in Figure 2 for the Random, Self and Yoked groups. Collapsing across all four targets for the Random and Self group comparisons, the only significant effect was a main effect of Exclusion, $F(1,36) = 8.89$, $p < .01$, $\eta_p^2 = .20$. Contrary to predictions, participants with performance-dependent target exclusion performed with more error in retention than participants without exclusion. The Random and Self groups did not differ, $F(1,36) = 1.59$, $p = 0.22$, $\eta_p^2 = 0.04$ and there was only a trend for an interaction between Schedule-type and Exclusion, $F(1,36) = 3.00$, $p = 0.09$, $\eta_p^2 = 0.08$. As seen in Figure 2, the exclusion effect was more pronounced for Self-control groups rather than Random groups. We also evaluated retention for each target individually (see Table 1, retention "test" means). For both the Random and Self groups, errors were generally higher for the Exclusion versus No-Exclusion groups for all targets. However, a significant main effect of exclusion was only seen for Target 1 (30° CCW). $F(1, 36) = 9.74$, $p < .01$, $\eta_p^2 = 0.21$ (Target 2, $F(1, 36) = 2.03$, $p = 0.16$, $\eta_p^2 = 0.05$, Target 3, $F(1, 36) = 3.80$, $p = 0.06$, $\eta_p^2 = 0.10$, Target 4, $F(1, 36) = 2.30$, $p = .14$, $\eta_p^2 = 0.06$). The only main effect of schedule-type was seen for Target 2 (alternating), $F(1, 36) = 5.85$, $p = .02$, $\eta_p^2 = .14$, due to increased error for Self vs. Random groups (all other Fs < 1).

We also ran secondary analyses to compare the Self and Yoked groups (also Figure 2, right side). Again, there was a significant effect for exclusion, $F(1, 36) = 12.74$, $p = 0.001$, $\eta_p^2 = 0.26$, where participants with exclusion performed with more error in retention compared to participants without exclusion. There were no main effects for schedule-type or interactions (Fs < 1). When examining each target individually (Table 1), Exclusion groups performed worse than No-Exclusion groups on Target 1 (30° CCW), $F(1, 36) = 7.77$, $p = 0.01$, $\eta_p^2 = 0.18$ and Target 3 (CW), $F(1,36) = 12.46$, $p = 0.001$, $\eta_p^2 = 0.26$ (Target 2, $F(1, 36) = 3.18$, $p = 0.08$, $\eta_p^2 = 0.08$, Target 4, $F < 1$). There was no main effect of schedule-type or interactions (all other Fs < 1.50)[2].

[2] To determine whether the exclusion effects may have been confounded by differences in switching amounts during practice (i.e., contextual interference), we included switching amount as a covariate in a follow-up analysis of retention data. There was still a significant main effect for exclusion $F(1,35) = 7.65$, $p = 0.009$ and no effects involving schedule-type when comparing the Random to the Self groups. Similarly, when comparing the Self to the Yoked groups, the main effect for exclusion was still present, $F(1,35) = 7.39$, $p = 0.01$ and there were no effects involving schedule-type.

3.2. Acquisition

Absolute error

Errors in acquisition as a function of block are displayed In Figure 3a for the Random and Self groups subdivided based on Exclusion group. Like retention, it was the No-Exclusion groups that had lower error than the Exclusion groups, $F(1, 36) = 17.91$, $p < .01$, $\eta_p^2 = .33$. There was only a trend for the Random groups to show less error than the Self-control groups, $F(1, 36) = 3.06$, $p = 0.09$, $\eta_p^2 = 0.08$. Schedule-type and Exclusion did not interact, $F<1$. There was a general decrease in error across blocks, $F(4.962, 178.64) = 11.83$, $p < .01$, $\eta_p^2 = .25$. Block interacted with both Schedule-type, $F(4.96, 178.64) = 6.28$, $p < .01$, $\eta_p^2 = .14$ and Exclusion group, $F(4.96, 178.64) = 2.89$, $p = .02$, $\eta_p^2 = .07$. Decrease in error was more pronounced in the Random rather than Self groups and in the No-Exclusion rather than the Exclusion groups. The 3-way interaction between Schedule-type, Exclusion and Block approached significance, $F(4.96, 178.64) = 2.15$, $p = 0.06$, $\eta_p^2 = 0.06$, due to the trend for the Random-Exclusion group to show greater decrease across the later blocks than the other groups (see Figure 3a).

Because each block of practice was based on aiming error for different targets, some of the improvements across practice are masked. Therefore, to better illustrate improvements with practice, we ran follow-up analyses with practice attempts divided into 3 blocks (Early, Middle, Late) with Target included as a factor (see Table 2 and Figure 4). There was a large main effect of target, $F(3, 108) = 232.03$, $p < 01$, $\eta_p^2 = .87$, with post hoc analysis confirming our expected target difficulty effects. Errors were lower to Target 4 (null) than to all other targets and errors were higher for Target 2 (alternating) compared to all other targets. Again there was a large block effect, $F(1.55, 55.67) = 178.45$, $p < .01$, $\eta_p^2 = .83$, but also a Target x Block interaction, $F(3.75, 135.08) = 35.36$, $p < .01$, $\eta_p^2 = .50$ as shown in Figure 4. Post hoc analysis showed that participants improved across all three acquisition blocks for Targets 1 and

3 (CW and CCW rotations), whereas for Targets 2 (alternating) and 4 (null), improvements were only seen when comparing early to late blocks.

In Figure 3b, acquisition error data across practice blocks for the two Yoked groups are shown (Exclusion/No-Exclusion), with the two Self-control groups for comparison. It was the No-Exclusion groups that again were more accurate in acquisition, $F(1, 36) = 14.14$, $p < 0.01$, $\eta_p^2 = .28$, but there was no main effect of schedule-type, nor a Schedule-type by Exclusion interaction (*F*s<1). Errors decreased across the twelve blocks $F(4.98, 179.25) = 3.99$, $p < 0.01$, $\eta_p^2 = .10$ and there was an interaction between Exclusion-group and Block, $F(4.98, 179.25) = 2.95$, $p = 0.014$, $\eta_p^2 = .08$. The No-Exclusion groups were more accurate than Exclusion groups on blocks 4-12 only. There was no Schedule-type X Block interaction nor a three-way interaction (*F*s <1).

Target attempts

Percentage of trials to each target as a function of control-group (Random and Self) are presented in Table 3 (note the Yoked groups were matched to the Self groups). Participants generally made more attempts to the more difficult than the easy target, $F(1.33, 47.77) = 86.64$, $p < 0.01$, $\eta_p^2 = 0.71$, with post hoc comparisons confirming differences between Target 2 (alternating) and Target 4 (null). There were also Target interactions with Schedule-type, $F(1.33, 47.77) = 6.75$, $p = 0.01$, $\eta_p^2 = 0.16$, and Exclusion-group, $F(1.33, 47.77) = 31.89$, $p < 0.01$, $\eta_p^2 = 0.47$. With the exception of Target 1 (CCW), post hoc analysis showed group differences in the number of trials to each target. Self-control groups had more attempts at the difficult target (Target 2) compared to the Random groups and Exclusion groups had more trials at this target than the No-Exclusion groups. For Target 3 (CW) and 4 (null), reversed effects were seen. Random groups had more trials than Self groups and No-Exclusion groups had more trials than Exclusion groups.

Switching

We were also interested in how individuals chose to complete practice (when they had choice) in terms of the degree of contextual interference (i.e., target switching) they bring into practice. This analysis was only completed for the Random and Self-control groups as a function of target. As shown in Figure 5, Random groups switched more (*M* = 140.55, *SD* = 14.18) than Self-control groups (*M* = 47.30, *SD* = 11.21), $F(1, 36) = 85.18$, $p < .01$, $\eta_p^2 = .70$ and No-Exclusion groups (*M* = 123.40, *SD* = 16.00) switched more than Exclusion groups (*M* = 64.45, *SD* = 14.89), $F(1, 36) = 34.04$, $p < .01$, $\eta_p^2 = .49$. Switching also depended on target, $F(2,39, 85.85) = 17.12$, $p < 0.01$, $\eta_p^2 = 0.32$. Based on post hoc tests, participants switched from the null Target 4 (*M* = 17.48 trials, *SD* = 17.22) less than all other targets and switched from the alternating Target 2 (*M* = 27.75 trials, *SD* = 18.66) more than Target 3 only (*M* = 22.68 trials, *SD* = 18.39; note Target 1, *M* = 26.03 trials, *SD* = 16.42). Although the Schedule-type X Exclusion interaction was not significant ($F = 2.43$, $p = 0.13$, $\eta_p^2 = 0.06$), there was a 3-way interaction with Target, $F(2.39, 85.85) = 5.11$, $p < 0.01$, $\eta_p^2 = .0.12$. In Figure 5 we have shown this interaction. Due to the forced schedule, the Random-No Exclusion group showed similar switching amounts to all four targets (just over 40 switches/target), but the Self, No Exclusion group also showed a similar parity across targets (although much reduced, ~15-20 switches/target). The Exclusion groups, particularly the Random-Exclusion group, showed a pattern of data across targets consistent with target difficulty; with low switching from Target 4 (null) and high switching from Target 2 (alternating).

Because switching amounts are confounded by number of trials to each target and we know that generally fewer trials were spent at the easier than difficult targets, interpreting these target switching effects were difficult. Therefore, we calculated percentage of trials where there was a switch away from each target as a function of the number of trial attempts. As expected, now we see a reversal in the pattern of data, with proportion of trials with a switch being higher for the easier target (*M* = 63%, *SD* = 24 %) and lower for the more difficult Target 2 (*M* = 34 %, *SD* = 30 %) and the intermediate difficulty targets showing the same relative amounts of switching (Target 1 & 2, *Ms* = 51%, *SDs* = 25 %). This was confirmed by a large target main effect, $F(2.36, 84.81) = 53.56$, $p<.001$, $\eta_p^2 = 0.60$ when these data were analyzed in a mixed design factorial ANOVA.

Participants in both Self-control and Yoked groups switched between targets in a performance-contingent manner, such that they were less errorful on trials before switching targets (*M* = 9.06°, *SD* = 3.08) than they were on repeat trials (*M* = 10.02°, *SD* = 3.64), as evidenced by a main effect of trial-type, $F(1, 36) = 10.00$, $p < .01$, $\eta_p^2 = .22$. We have plotted these data as a function of Schedule-type and Exclusion-group in Figure 6. Although there was the previously shown target effects associated with higher error for the alternating target and lower error for the null target, Target did not interact with Trial-type ($F < 1$). There were also no other interactions involving Trial-type, although the Exclusion group X Trial-type interaction showed a trend, $F(1, 36) = 3.47$, $p = 0.07$, $\eta_p^2 = .09$. This trend was mainly due to more pronounced differences for the No-Exclusion rather than Exclusion groups (Schedule-type X Exclusion X Trial-type, $F = 1.92$, $p = 0.17$, all other interactions with Trial-type, $Fs < 1$).

Finally, to explore whether individual differences in overall switching amounts were related to learning, we correlated the total number of switch trials in acquisition to absolute error in retention. Scatter plot data for the six groups are shown in Figures 7a-c. The expected negative correlation was seen for the Self, No-Exclusion group (Figure 7a), although it only accounted for 14 % of the variance in retention error ($r = -.38$, which was not statistically significant). Generally, more switching was associated with lower retention error. Exclusion led to fewer switch trials, which moderated the expected relationship between switching and error for the Self, Exclusion group. Indeed, there was a trend for a positive correlation ($r = .43$), mostly driven by one participant who showed a lot of switching (more than twice that of others). This person had one of the highest errors in retention, suggesting that this more random strategy coupled with target exclusion of the easier targets harmed overall learning. In Figure 7b, the yoked participants are shown. For the No-Exclusion group, there was no relationship between switching amount and error. For the Yoked, Exclusion group, a trend for a small negative correlation was seen (r = -.26, ns), but again, the individual who had twice as much switching as others, appeared to violate this trend. Looking at the two Random groups in Figure 7c, not surprisingly the Random, No-Exclusion group showed little variability in switching due to the fixed schedule, but showed a trend for a positive correlation (r = .32, ns). The Random, Exclusion group also showed a trend for a positive correlation (r = .53, p =.12), with more switching associated with increased error.

4. Discussion

We studied the effects of performance-dependent target exclusion on learning to determine whether an uncertainty-based selection strategy encouraged by exclusion was optimal for learning (Huang et al., 2008). Our results did not show support for the benefits of this strategy; neither when exclusion was enforced nor when individuals were allowed to choose how to practice. Despite the fact that learners in the exclusion groups practised the difficult target the most and the easiest target the least, participants that were subject to target exclusion performed worst in retention overall. Although excluding targets based on consistent low error was detrimental to learning, when individuals were given choice over how to practise, they adopted a strategy consistent with a less extreme uncertainty-based method. Fewer trials were spent on the easier targets, but they continued to return to these targets throughout practice .

In the discussion of these results, we attempt to answer the following questions: what is (or are) the mechanism(s) by which target exclusion hurts learning (or return to easier targets improves learning), what are the characteristics of self-directed practice choices in terms of target difficulty and error and related, why is self-directed practice not different to random practice nor yoked conditions and finally, what are the implications of these data for organizing practice of different skill components and what does this mean for motor learning theory?

4.1. Mechanisms by which target exclusion hurts learning

When comparing across the Random and Self groups, as well as comparing the Self groups to the Yoked groups, exclusion group effects were consistently shown. These effects accounted for ~20-30 % of the unexplained variance in the respective ANOVAs for acquisition and retention. Exclusion of task components based on consistent high accuracy (in our case, five consecutive trials of low error), was not a useful learning method. A consequence of this exclusion method was that individuals were forced to spend time on more difficult task components during practice (between ~63-73% for the Exclusion groups, in comparison to ~25-46% for No-Exclusion groups on the most difficult target). Therefore, exclusion participants did not get as frequent opportunities to achieve low error scores in practice and hence had higher error in this phase. Having to be tested on four targets in retention, in a random order, would still mean that individuals would need to remember that the easy Target 4 was a non-adapted movement and with less practice switching to this target in acquisition, there may have been some forgetting when returning to this target in retention. There is also research to suggest that overpractising (termed overlearning), has small benefits for retention of physical tasks, although the reasons for these effects are debated. Practising beyond mastery, even if at the expense of practice on more difficult task components, might produce a more established memory (Driskell et al., 1992). Despite these conjectures, it is important to note that the effects of exclusion in retention were not limited to higher error for the exclusion groups on the easier targets. For example, the difference for Target 4 (null) in retention, comparing across the Exclusion and No-Exclusion groups, was ~.32 degrees, whereas the overall group difference, irrespective of target, was 1.54 degrees.

Another potential reason for differences among exclusion groups could be due to the reduced opportunity to practice some of the easier-to-medium difficulty targets and switch between these targets, resulting in lower CI. Although individuals could still switch throughout most of practice, there were fewer targets to switch to/from and these targets would be of high(er) difficulty. Indeed, participants in the Exclusion groups showed almost half the amount of switching between targets than those in the No-Exclusion groups. Therefore, this exclusion strategy encouraged a more blocked style of practice, which has repeatedly been shown to be less effective for overall task retention in comparison to a schedule high in switching/interference (see Lee, 2012; Wright & Kim, 2020 for recent reviews). However, the amount of switching did not remove exclusion effects when we included it as a covariate in follow-up analyses. It is also worth noting that the schedule of switching that generally characterized the exclusion groups, was one where they gradually progressed to a low variability, more blocked schedule (i.e., only one or two targets to practise) from an early more variable, random schedule. There is evidence that the reverse type of schedule is actually a more effective learning schedule, where individuals progress from early blocked practice to more random practice once task components are mastered (e.g., Albaret & Thon, 1998; Hodges et al., 2011; Landin & Hebert, 1997; Porter & Magill, 2010). Therefore, it is possible that target exclusion effects were related to the reduction of variability in target choice and in some cases target order, rather than the absolute amount of CI.

Another variable which could explain the target exclusion effects could be related to motivation and the lack of reward associated with return to a target which has a high degree of success. There is evidence that target success in acquisition is beneficially related to learning outcomes, even when successes are manifested as positive feedback in comparison to others or in comparison to trials which are not as successful (e.g., Abbas & North, 2018; Badami et al., 2012; Carter et al., 2016; Chiviacowsky & Wulf, 2007; Saemi et al., 2012). The mechanism behind these success-manipulation effects is thought to be related to release of dopamine and better consolidation of motor memories (Wulf & Lewthwaite, 2016). We did not take measures of motivation in this experiment so we can only speculate as to whether individuals experienced the Exclusion conditions as less motivating than the No-Exclusion conditions. There is likely a balance needed between optimization of challenge, and uncertainty for learning through information potential, and motivational costs which could ensue from a more errorful practice (Hodges & Lohse, submitted; Hodges & Lohse, 2020). We do know in other work that self-control participants choose to receive outcome feedback on trials where they are performing relatively accurately, versus low accuracy trials (e.g., Chiviacowsky & Wulf, 2002). The heightened motivation from reinforcing of good performance has been suggested to be the reason why this behaviour is seen and could also explain why individuals also choose to return to already mastered targets in our study.

In summary, there appears to be benefits associated with return to easier targets, rather than adoption of uncertainty-based practice methods, where easier task components are excluded from practice. Although we are unsure as to what the exact mechanism is that is driving negative effects of exclusion, we speculate that it is likely to be a combination of reduced switching behaviours, especially later in practice, and reduced motivation or engagement on the task associated with low target successes. In the final section on theory, we consider the challenge-point framework as an alternative framework for explaining these target exclusion effects and the fact that practice of only difficult targets would create suboptimal challenge through too much uncertainty.

4.2. Self-directed practice choices

We did not observe any beneficial effects associated with self-control in acquisition or retention. Despite the fact that the self-control groups and the random groups had drastically different switching amounts and differed in their number of attempts to each target, there was little difference between these groups in terms of overall accuracy. The Random, No-Exclusion group experienced high contextual interference (~40 switches/target), as a result of their enforced schedule, whereas the Self, No-Exclusion group had less than half this amount (~15 switches/target). These data show that having control over practice mitigates potential costs associated with a more blocked practice schedule and is consistent with other literature on self-controlled practice (e.g., Hodges et al., 2011, 2014; Wadden et al., 2019; Wu & Magill, 2011).

The self-control groups were also compared to yoked groups, where the schedules were matched in terms of order of practice and target difficulty. Here, we also did not see accuracy advantages associated with self-controlled practice. This may be because the schedule of target switches imposed on the yoked partner also appeared to incidentally follow a performance-dependent schedule, particularly for the No-Exclusion groups (see Figure 6). In general, there was more switching after low error trials in comparison to relatively high error trials, evidenced by a main effect of switch/repeat trial-type but no group-related main effects or interactions. This pattern of switching, where trials are repeated when errors are relatively high and switched when errors are relatively low, is a common finding in the self-control of practice literature (e.g., Hodges et al., 2014; Keetch & Lee, 2007).

We did see a small, negative relationship between the amount of switching and absolute error in retention for the Self, No-Exclusion group, but not their yoked counterparts (Figure 7a & b). For the Self, No-Exclusion group, there was a trend for greater switching to be associated with less error, which is consistent with the CI literature (e.g., Wu & Magill, 2011). Although the two individuals who showed the most switching were among the top four performers in retention, the difference in degrees was less than 1 between the person who showed the most switching (135 times) and the person who showed the least (15 times). For the Self and Yoked groups, the amount of switching or CI had only a small influence on overall learning in this task. It is more likely that what was practised, rather than (or in addition to) when to change practice, had the most influence on learning.

Surprisingly, for the Self, Exclusion group, a small positive correlation was observed between switching and retention error, although the trend seemed to be driven by one individual. In general, the amount of switching was relatively low in this group (between 5 and 43 times), suggesting that exclusion moderated decisions to switch, perhaps because of the reduction in choice. However, one individual switched 97 times and they showed the second highest error. Constant switching between targets of medium to high difficulty may create too much uncertainty and challenge in comparison to high amounts of switching between easy to medium difficulty targets. Similarly, for the Yoked, Exclusion participant who was matched to this high switching schedule, they also bucked the trend for a decrease in error as switching increased. Random groups that had high amounts of enforced switching also showed similar trends for positive correlations between switching amount and retention error, despite low variability in switching between participants. These correlations support the suggestion that too much switching, when the task/targets are of high difficulty, is bad for learning. This suggestion is wholly consistent with the challenge-point hypothesis, whereby too much challenge/uncertainty is as bad for learning as too little (Guadagnoli & Lee, 2004).

4.3. Study limitations

While this experiment yielded some surprising results, it is important to consider the limitations of these data. We purposefully chose a task and targets that were unlikely to generalize across the different task components (i.e., targets that were associated with different rotations such that improving on a clockwise rotation would not positively transfer to a counterclockwise rotation; e.g., Krakauer et al., 1999; Larssen et al., 2012). As such, there was high variation between the targets, the task was relatively difficult, and the amount of learning was compromised. Although we showed improvements across practice for all targets, Target 2 (alternating) was clearly difficult and only showed improvement when we compared early practice trials with late practice trials. At the other extreme, Target 4 was easy as there was no rotation to the feedback, leading to little improvement with practice. It remains to be tested whether target exclusion effects would potentially be more positive if targets were more similar in difficulty or extended practice was given, such that exclusion would happen later in practice and success would be attainable on all targets.

Visuomotor adaptation tasks require only an adjustment to motor plans, typically acting on sensory prediction and more implicit motor learning processes (e.g., Mazzoni & Krakauer, 2006; Mcdougle et al., 2016). It will be informative in future work to not only test the generalization of these effects across tasks, but to better probe mechanisms underpinning successful adaptation in this task. Unintentional after-effects to targets when the rotations are removed, give an indication of implicitly acquired processes associated with sensory predictions. Such measures, would be informative as to how learning was achieved and whether certain conditions, such as target exclusion or more switching between targets promotes more implicit learning (e.g., Dang et al., 2019).

Another potential limitation was the choice of our exclusion criteria (i.e., low error at a target on five successive trials), which may not have fostered or reflected 'mastery'. Huang et al. (2008) suggested that repeating a target after experiencing low error was suboptimal, but they did not advocate a target exclusion method. As such, it is likely that this method of outright exclusion of targets and the prevention of practice on easier subcomponents, rather than the principle of uncertainty-based selection itself, that is questionable. In previous work using win-shift, lose-stay methods of task selection (e.g., Simon et al., 2008), success was based on low error on only one or two trials. Hence, in our experiment, we did have more stringent methods for determining "success". However, in these other task selection strategies, individuals were able to return to these successful targets which was not an option in ours. However, in neither of the win-shift, lose-stay studies we detail in our introduction, were beneficial learning effects noted when compared to random or yoked-schedule comparison groups (Porter et al., 2019; Simon et al., 2008).

Target exclusion generally has the effect of reducing participant's self-control of practice. By the end of acquisition, the Self-Exclusion group is no longer making decisions about their own practice and is, in effect, forced into a mode of practice. Thus, participants in this group are not subject to a truly self-determined schedule of practice. In fact, this may have negative consequences for learning where choice is now removed. As far as we are aware, this removal of choice in a motor learning study has not been studied, but it may be that the negative consequences associated with removal of choice outweigh the potential benefits associated with giving choice. According to OPTIMAL theory, there are direct and indirect consequences associated with the provision of choice on motor learning, which may work through an increase in task engagement and ultimately enhanced memory consolidation (Wulf & Lewthwaite, 2016). However, research is needed to study the effects of choice removal on learning to better isolate if and how autonomy-removal impacts learning, perhaps through a simple cross-over design where choice over practice decisions is either given or not early in practice and removed (or not), later in practice.

4.4. Conclusions and implications for theory

Our aim in running this experiment was to determine whether an uncertainty-based practice schedule (Huang et al., 2008), which in this experiment was operationalized as exclusion of easy task components, would be a beneficial practice method for learning. We were also interested in determining whether individuals given choice adopt an uncertainty-based method of practice. Although target exclusion did not benefit learning and in fact was harmful relative to no-exclusion, participants given choice over their schedule chose to adopt a schedule of practice that veered towards uncertainty-based selection. The Self, No-Exclusion group allocated the most practice to the highest difficulty target and the least practice to the lowest difficulty target. Further, the self-control learners without exclusion switched more on low error than high error trials. Therefore, individuals reduce the tendency to repeat well-performed task components, but they do not remove this tendency completely. Rather, there appears to be benefits associated with returning to “easier” or low error task components. The Self, No-Exclusion group spent 12 % of their practice time on the easiest target, in comparison to the Self and Random, Exclusion groups that spent less than 4 %. It is important to point out that Huang et al. (2008) did not implement an exclusion paradigm in their study, but rather showed benefits associated with such a strategy and recommended the use of an artificial coach to instruct learners to practise in accordance with uncertainty-based selection. Based on our data, it appears that even without this coach, learners choose to adopt a weak form of such a strategy. However, this schedule does not aid retention more than that observed for individuals who spend an equal amount of practice trials at all four targets, at least if these are practised in a random order.

In returning to the challenge-point framework as a way of understanding conditions which promote or potentially hinder learning, it is important to consider the amount of information available from the learning situation as a function of the individual learner, what is referred to as functional task difficulty (Guadagnoli & Lee, 2004). In our experiment, the nominal difficulty of the tasks (targets) was manipulated, with easier and more difficult targets as confirmed by our error data on these targets. Target exclusion, however, was based on functional task difficulty (i.e., participant’s own error). Uncertainty increased in an individualized manner in the target exclusion conditions, but the data show that this method degraded rather than optimized learning. Although it is possible that the functional task difficulty manipulations were not optimal (and as discussed above, potentially the criteria was too lax for determining target success), these data also argue for some interpretation of “certainty” based practice benefits in the challenge-point framework. Perhaps uncertainty and information need to be considered with respect to expectations for success or rewards, with optimal challenge being based on both information gain and maintenance of existing skills (Hodges & Lohse, submitted; Hodges & Lohse, 2020). There may be a necessity to have some positive rewards when practising tasks with complex task components to promote learning (e.g., Lohse et al., 2020; Ma et al., 2017). It may also be helpful to consider optimal challenge as conditions which provide a mix of challenges, including some low, some medium and some high, rather than all medium to high. For the Self, No-Exclusion group, more switching (i.e., higher challenge practice), was associated with lower error, as would be expected based on traditional CI effects. However, this negative trend was not the case for other practice conditions, especially when switching amounts were high. For both Random groups, positive correlations were seen between switching amounts and retention error. One participant in the Self, Exclusion group showed a particularly high amount of switching compared to others in that group, which was also associated with high error. A similar pattern was also seen for their yoked counterpart. High switching between only medium to difficult targets has learning costs. It is likely that the functional difficulty and hence challenge is too high when nominally high target difficulty is combined with a high task switching schedule

In conclusion, removing target choice of easy or seemingly mastered task components during a practice session is not a good method for motor learning, but rather there appears to be benefits associated with allowing learners to return to components of a task that are relatively easy. These benefits are seen in groups that are given control over practice, but also in groups that are not (Random and Yoked). Moreover, these benefits are seen in groups that practise with high amounts of CI (i.e., Random), as well as in groups where CI is comparatively lower (i.e., Self and Yoked). Thus, we recommend allowing learners to practise easy task components and not enforcing any schedule of practice which would deny this opportunity. Certainty-based practice appears to have some benefits for learning, if part of a more challenging series of tasks or skills, as long as time is divided between easy and difficult task components.

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Table 1. Mean absolute error (in degrees) reported for individual targets (1-4) during practice and the retention "Test". Standard deviation of the mean (SD) are in parentheses. All means and SDs are reported as a function of Control (Random, Self, Yoked) and Exclusion group.

Group/Control		Target 1		Target 2		Target 3		Target 4	
		Practice	**Test**	Practice	**Test**	Practice	**Test**	Practice	**Test**
Random	Exclusion	14.27	**11.04**	14.54	**15.45**	11.16	**9.49**	7.30	**3.82**
		(8.75)	(5.73)	(6.87)	(6.41)	(6.13)	(5.48)	(7.76)	(3.66)
	No-Exclusion	11.23	**8.97**	16.63	**16.71**	10.40	**8.32**	4.55	**3.71**
		(8.45)	(6.95)	(6.17)	(6.40)	(6.18)	(4.77)	(11.66)	(3.08)
Self-Control	Exclusion	11.69	**13.42**	15.76	**17.21**	11.19	**9.84**	4.42	**4.33**
		(8.83)	(8.32)	(6.68)	(5.23)	(8.74)	(5.44)	(3.95)	(3.29)
	No-Exclusion	10.03	**8.72**	17.10	**17.40**	8.00	**7.48**	4.49	**3.24**
		(8.48)	(6.85)	(5.46)	(7.02)	(6.40)	(5.25)	(4.46)	(3.01)
Yoked	Exclusion	10.04	**11.95**	16.33	**15.92**	11.85	**12.72**	4.63	**3.98**
		(7.25)	(8.56)	(5.74)	(7.70)	(8.68)	(6.57)	(5.25)	(3.52)
	No-Exclusion	10.91	**8.88**	14.60	**15.76**	8.04	**7.30**	4.27	**4.22**
		(8.72)	(5.62)	(7.22)	7.60	(7.82)	(5.64)	(3.90)	(3.35)

Table 2. Mean absolute error (in degrees) reported for individual targets (1-4) in early, middle, and late acquisition blocks. Standard deviation of the mean (SD) are in parentheses. All means and SDs are reported as a function of Control (Random, Self) and Exclusion.

Group/Control		Target 1			Target 2			Target 3			Target 4		
		Early	Middle	Late	Early	Middle	Late	Early	Middle	Late	Early	Middle	Late
Random	Exclusion	21.25	11.64	9.62	16.77	14.71	13.16	16.73	10.75	6.14	5.81	5.15	4.38
		(3.69)	(3.76)	(3.75)	(0.89)	(3.59)	(4.77)	(3.41)	(2.84)	(1.86)	(4.41)	(4.24)	(3.45)
	No-Exclusion	16.76	10.52	6.43	16.84	17.12	15.94	15.50	9.34	6.34	6.28	4.07	3.31
		(4.28)	(4.03)	(1.81)	(0.99)	(1.27)	(0.79)	(2.35)	(1.84)	(2.10)	(4.43)	(1.13)	(0.87)
Self-Control	Exclusion	18.49	11.00	6.26	17.09	15.61	15.28	19.63	10.22	5.12	5.36	3.66	3.23
		(5.35)	(4.38)	(3.33)	(1.90)	(3.18)	(3.27)	(4.94)	(3.71)	(1.69)	(3.07)	(1.79)	(2.00)
	No-Exclusion	13.49	8.93	8.44	17.87	16.84	16.85	11.82	6.88	6.02	4.90	3.62	4.43
		(4.45)	(2.27)	(2.47)	(0.94)	(0.69)	(0.96)	(2.28)	(2.61)	(1.99)	(2.43)	(1.66)	(1.52)

Table 3: Mean percentage of trials to each target as a function of Control (Random, Self) and Exclusion group. Standard deviations of the mean (in parentheses) and range (min – max in italics) are reported for each target.

Groups/Target		Target 1 (+30CW)	Target 2 (alternating)	Target 3 (-30CCW)	Target 4 (null)
Random	Exclusion	18.25 (6.56)	63.42 (16.32)	14.42 (11.46)	3.92 (3.99)
		9.2 – 29.2	*37.5 – 80.4*	*5.8 – 36.3*	*2.1 – 15.0*
	No-Exclusion	25 (0)	25 (0)	25 (0)	25 (0)
		NA	NA	NA	NA
Self-Control	Exclusion	17.54 (19.06)	72.46 (20.79)	7.13 (3.98)	2.88 (1.23)
		2.9 – 60.0	*29.2 – 90.0*	*3.8 – 17.5*	*2.1 – 5.8*
	No-Exclusion	22.13 (7.25)	45.67 (20.27)	20.13 (7.49)	12.08 (6.85)
		11.7 - 32.9	*12.9 – 75.8*	*7.5 – 29.6*	*3.8 – 25.4*

Figure captions

Figure 1: Schematic of the target array with direction and magnitude of cursor rotation detailed.

Figure 2. Mean absolute aiming error (in degrees) during the 24-hr retention test plotted as a function of Exclusion for the Random, Self-Control and Yoked conditions. Means for all participants in each exclusion condition are represented by bars. Error bars are standard error of the mean. Individual participant means are represented by the individual data points. Self-control participants' aiming error was compared to Random (primary analysis) and Yoked participants' (secondary analysis).

Figure 3a and b: Mean absolute error (degrees) for the (a) Random and Self groups (Exclusion and No-Exclusion) and (b) Yoked and Self groups (Exclusion and No-Exclusion) across the 12 blocks of acquisition (error bars are standard error of the mean).

Figure 4: Mean absolute error (degrees) across Early, Middle and Late acquisition for each target (error bars are standard error of the mean).

Figure 5: Mean absolute number of switches from each target for the Random and Self groups as a function of Exclusion and No-Exclusion conditions (error bars are standard error of the mean).

Figure 6. Mean absolute error (degrees) on repeat or switch decision trials during acquisition for the Self and Yoked groups, for both Exclusion and No-Exclusion groups. Means for all participants in each exclusion condition are represented by bars. Error bars are standard error of the mean. Individual participant means are represented by the individual data points.

Figure 7a-c: Scatterplots to show the relationship between switching amount and absolute error in retention (degrees) for the Self-control (a), Yoked (b) and Random (c), No-Exclusion (black symbols and trendline) and Exclusion groups (open symbols and dashed trend lines).

Figures

Fig 1

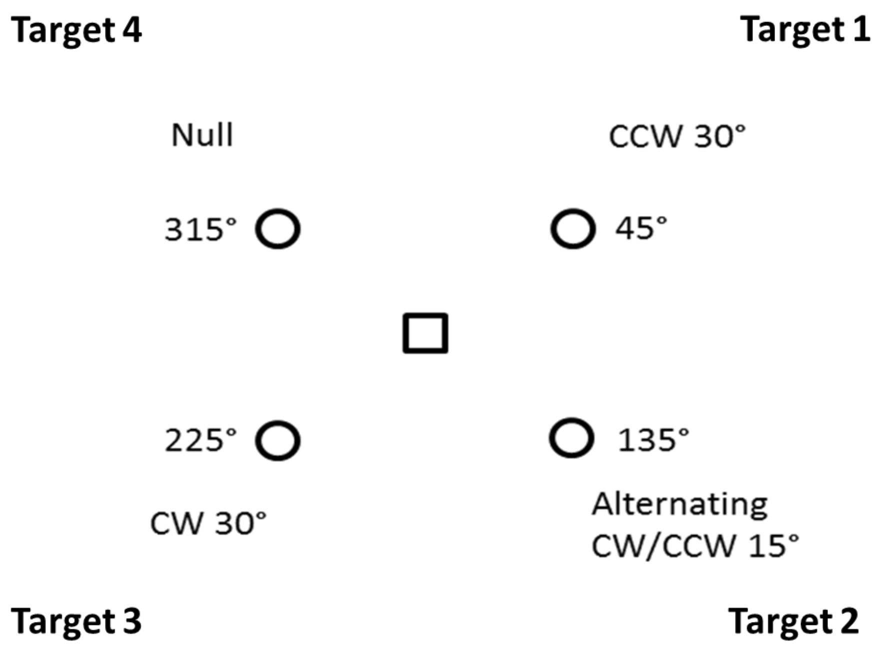


Fig 2

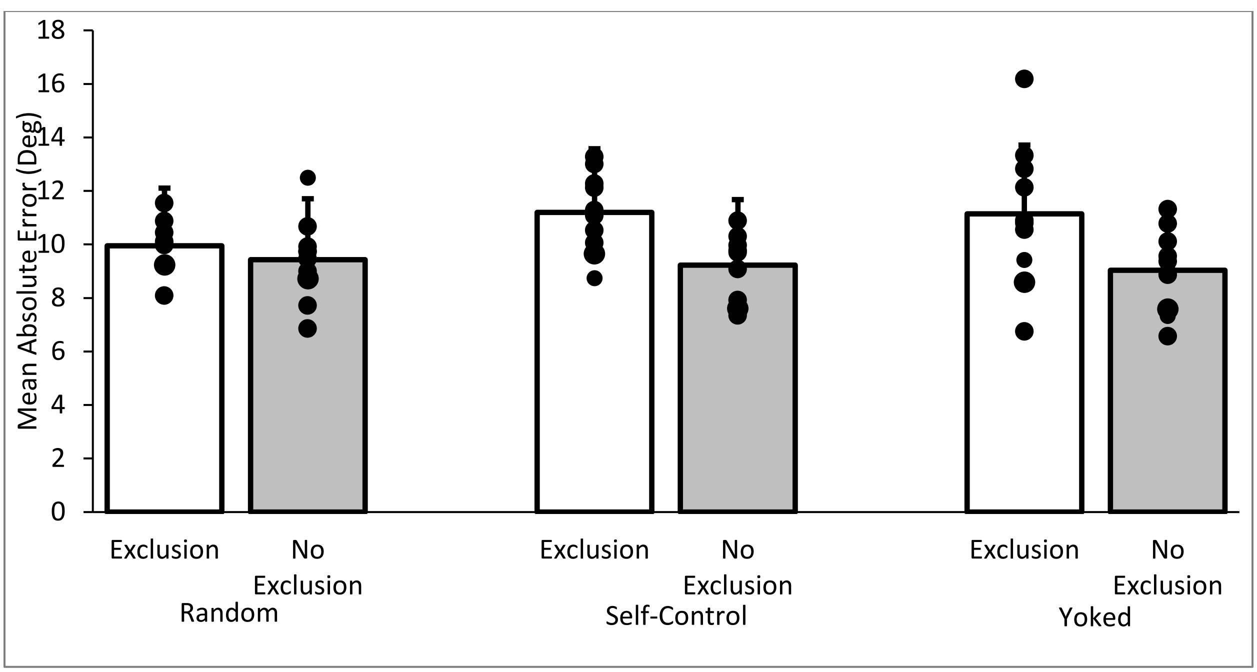


Fig 3a

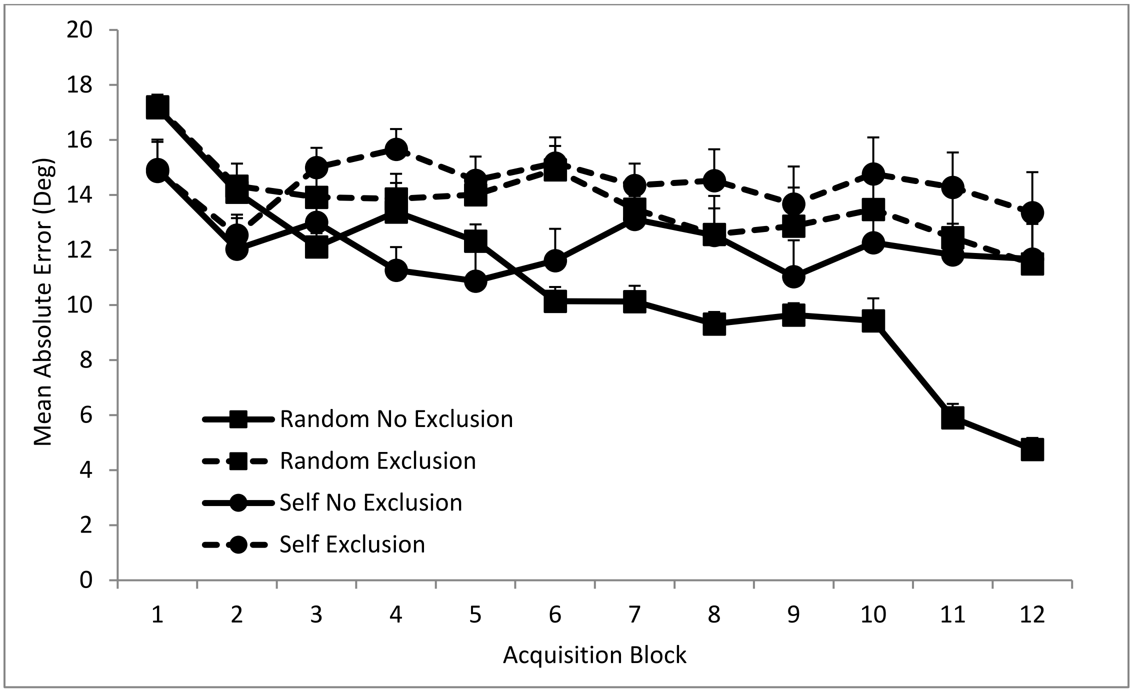

Mean Absolute Error (Deg)
Acquisition Block
Random No Exclusion
Random Exclusion
Self No Exclusion
Self Exclusion

Fig 3b

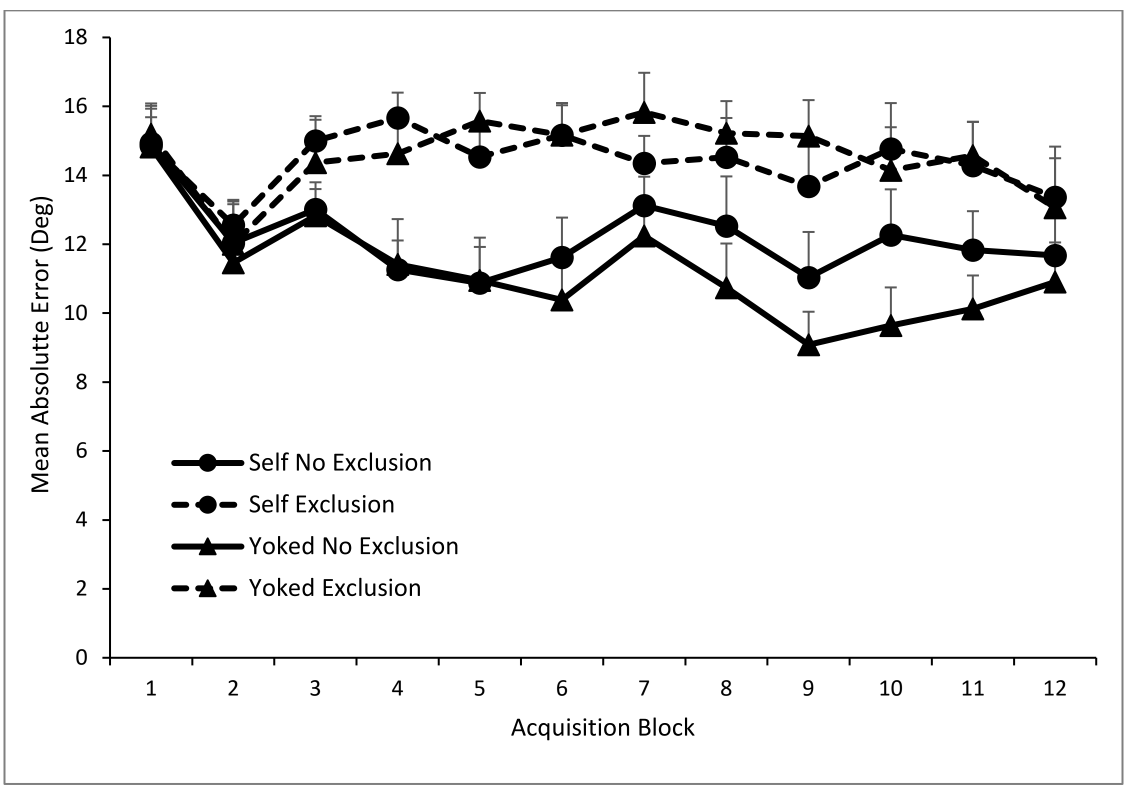

Mean Absolutte Error (Deg)
Acquisition Block
Self No Exclusion
Self Exclusion
Yoked No Exclusion
Yoked Exclusion

Fig 4

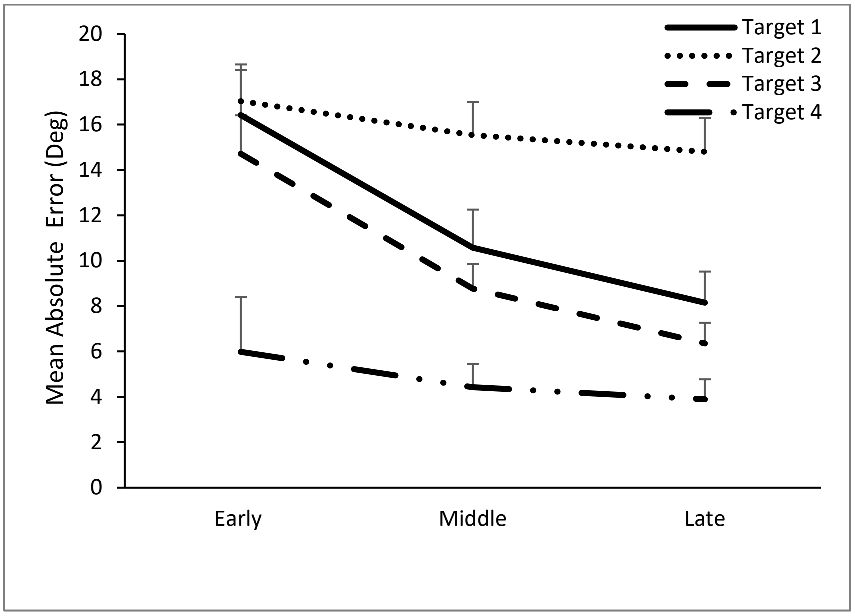

Target 1
Target 2
Target 3
Target 4
Mean Absolute Error (Deg)
20
18
16
14
12
10
8
6
4
2
0
Early
Middle
Late

Fig 5

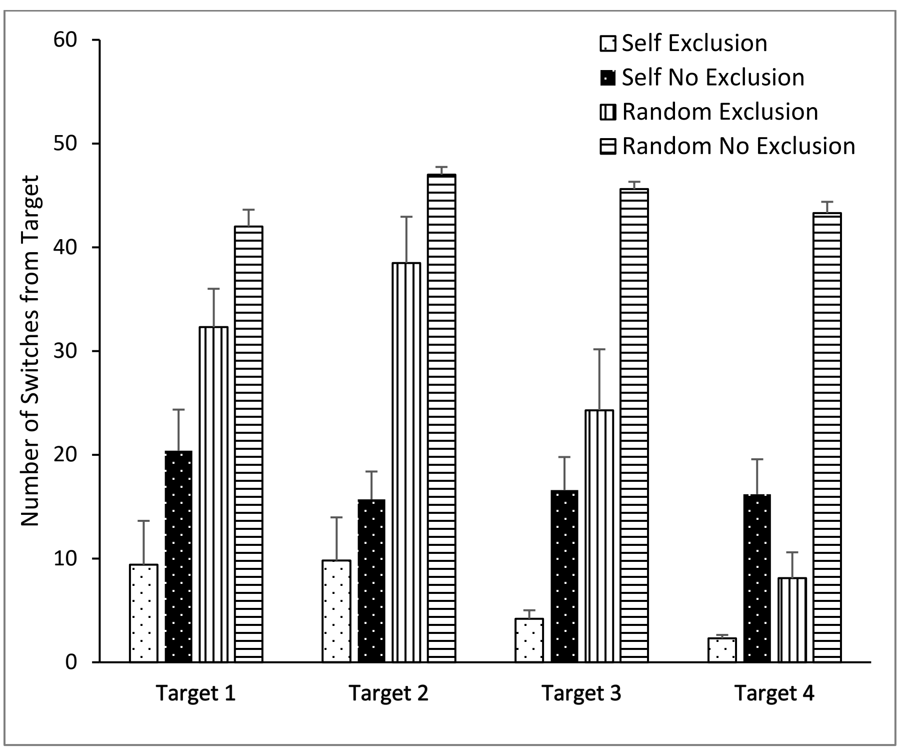
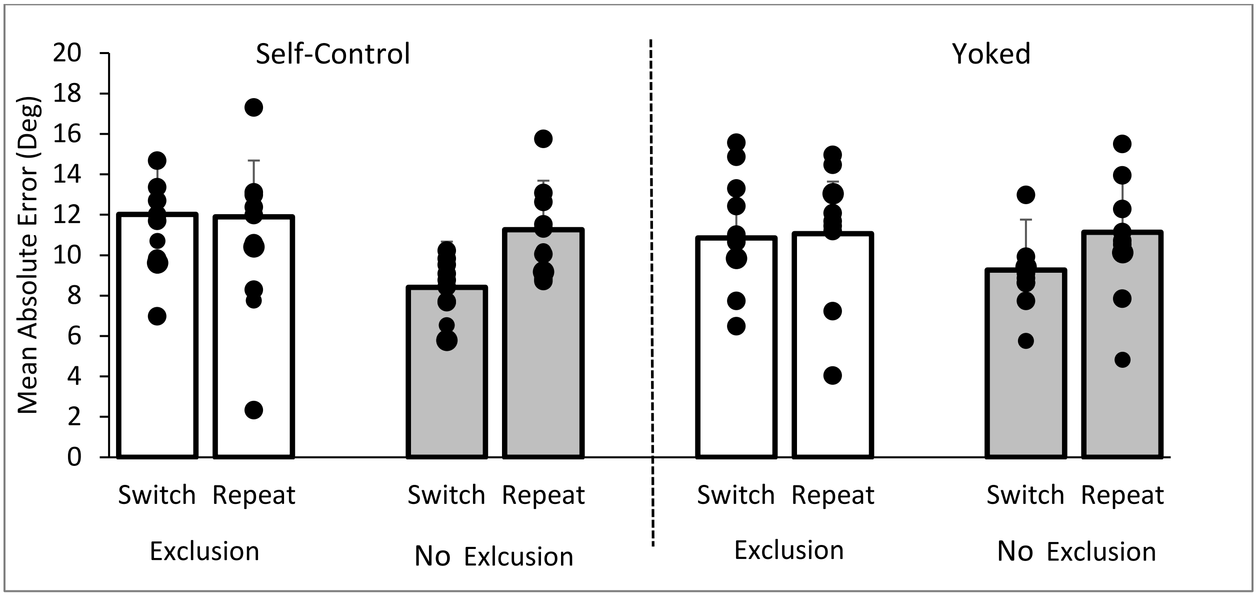
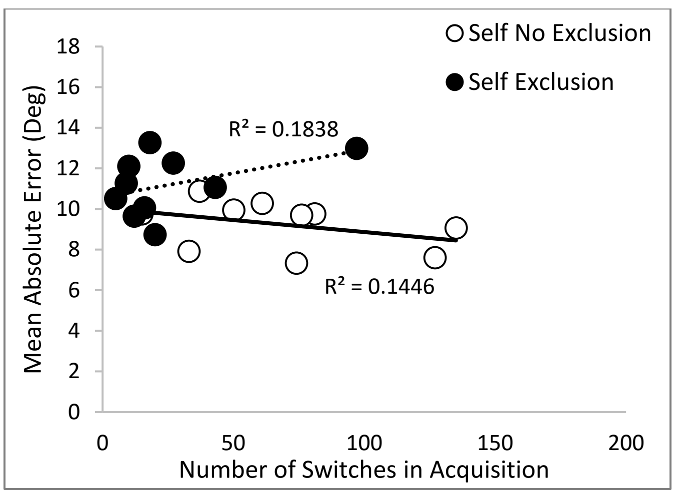

Self Exclusion
Self No Exclusion
Random Exclusion
Random No Exclusion
Number of Switches from Target
60
50
40
30
20
10
0
Target 1
Target 2
Target 3
Target 4

Fig 6



Self-Control
Yoked
Mean Absolute Error (Deg)
20
18
16
14
12
10
8
6
4
2
0
Switch Repeat
Switch Repeat
Switch Repeat
Switch Repeat
Exclusion
No Exlcusion
Exclusion
No Exclusion

Fig 7a



Self No Exclusion
Self Exclusion
$R^2 = 0.1838$
$R^2 = 0.1446$
Mean Absolute Error (Deg)
18
16
14
12
10
8
6
4
2
0
0
50
100
150
200
Number of Switches in Acquisition

Fig 7b

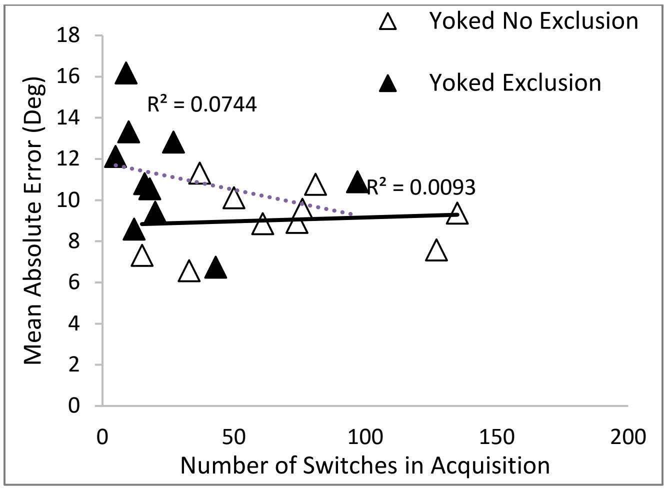
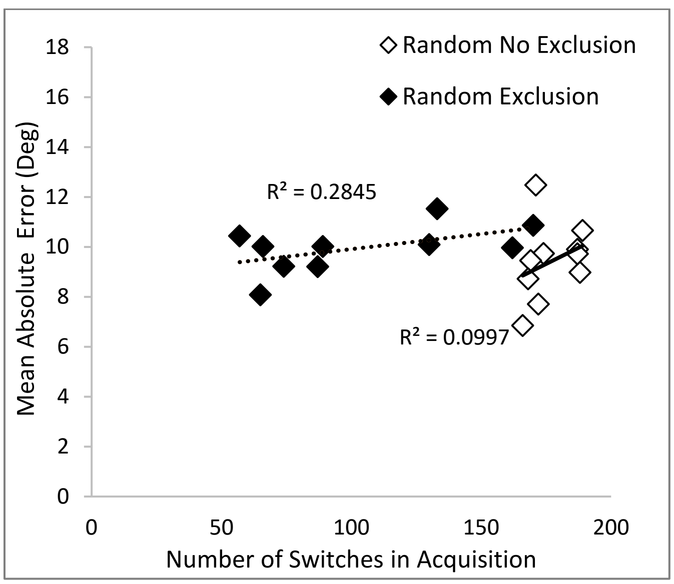

Yoked No Exclusion
Yoked Exclusion
R² = 0.0744
R² = 0.0093
Mean Absolute Error (Deg)
Number of Switches in Acquisition
0
2
4
6
8
10
12
14
16
18
0
50
100
150
200

Fig 7c


Random No Exclusion
Random Exclusion
R² = 0.2845
R² = 0.0997
Mean Absolute Error (Deg)
Number of Switches in Acquisition
0
2
4
6
8
10
12
14
16
18
0
50
100
150
200