SELF-REGULATED PRACTICE, TASK COMPLEXITY, AND MOTOR LEARNING

THE EFFECT OF SELF-REGULATED PRACTICE ON MOTOR LEARNING USING TASKS OF VARYING COMPLEXITY

By

KATHERINE M KEETCH, H.B.KIN.

A Thesis

Submitted to the School of Graduate Studies

in Partial Fulfillment of the Requirements

for the Degree of Master of Science

McMaster University

MASTER OF SCIENCE (2005) McMaster University

(Kinesiology) Hamilton, Ontario

TITLE: The Effect of Self-Regulated Practice on Motor Learning using Tasks of Varying Complexity

AUTHOR: Katherine M Keetch, H.B.Kin. (McMaster University)

SUPERVISOR: Professor Timothy D Lee, Ph.D.

NUMBER OF PAGES: ix, 87

Abstract

Increasing evidence indicates that giving individuals control over their practice schedule facilitates motor learning (Titzer, Shea, & Romack, 1993; Wu & Magill, 2004, 2005). A recent study within cognitive psychology (Son, 2004) found that individuals massed practice on tasks they judged as hard but spaced practice on tasks they judged as easy. The purpose of this experiment was to examine how self-regulated practice impacts motor learning and the strategies used by individuals as a function of task complexity. Participants were required to move a mouse-driven cursor through a pattern of coloured squares, pausing only long enough in each square to make an appropriate button press (white square=left button, black square=right button). Task complexity (4 easy and 4 hard patterns) was determined by the combined effects of the arrangement of the grid of squares and the hand used to manipulate the mouse (easy =dominant hand, hard=non-dominant hand). Participants were randomly assigned to one of eight groups: blocked, random, self-regulated, and yoked to self-regulated, performing either the easy or hard tasks. The number of switches between patterns were recorded as well as temporal and accuracy measures. The self-regulated groups were ineffective in acquisition, but showed the most stable and improved performance in retention, irrespective of task difficulty. Moreover, although switch strategies of the self-regulated groups differed between and within task complexity, the motor learning advantage was generalized. Taken together, these results reveal that an individual's strategic approach to practice may change as a function of task complexity, with no detriment to motor learning and adds to the growing body of literature that suggests self-regulated practice is an important variable for effective motor learning.

Acknowledgements

So many people to thank, so little time (and room on this page!). Well, first and foremost, I would like to thank Tim for all his support, insight, and passion for learning. If it was not for you, I would not have come into graduate school in the first place. I also would like to thank Dig for his continued encouragement, guidance, and laughter. If it was not for you, I probably would not have decided to stay in academia. Special thanks also to Jim, whose wit always keeps me on my toes and in my head and thanks too to Jan for being a part of my committee. I would also like to thank my family (immediate and extended) for always being there for me, and for supporting me in whatever way you could along the way and in all the ways that count. Cheryl, Clare, Melinda, Vicky, Courtney, SteVe, Hansen, Cullen, Claudia, Jocelyn, Suzanne, Klimstra, Jae (so basically everyone I've ever met in the lab), thank you SO much for all the good times, quotes of the day, challenges, conversations, and genuine friendship over the last two years. A big *bop bop* goes out to all my friends outside of academia: Ian, Carissa, Jenn, Kenz, and Dale, who may not know what the heck I'm talking about most the time but are proud of me anyway. I'd especially like to thank, Lynn, for being my mentor, longest and truest friend. And last but certainly not least, I would like to thank my Alexis. Thank you for your understanding, unwavering support, and for knowing everything about me and loving me anyway. And thank you for being my biggest fan.

Table of Contents

List of Tables

List of Figures

Introduction

One goal of motor learning research is to identify factors that influence optimal acquisition of motor skills, and in so doing, better understand the underlying processes that result in these improvements. The learning process is far from simple and how any particular motor skill develops has been shown to depend on many variables (For a review on practice scheduling, see Magill & Hall, 1990. For a review on augmented feedback, see Magill, 2001. For a review on task characteristics, see Wulf & Shea, 2002). Although many factors are important and contribute to motor learning, how practice is organized has a particularly powerful influence on motor acquisition and retention. Indeed, an extensive amount of research has investigated how practice conditions can be optimized to achieve maximal learning. In this context, the following thesis examined how giving individuals control over their practice organization impacted motor learning when performing tasks of varying complexity.

How Should One Schedule Practice?

Over the last three decades perhaps the most popular research topic related to practice scheduling has compared the effects of random versus blocked practice (commonly termed the "contextual interference" or CI effect). Shea and Morgan (1979; although see Battig, 1978) first studied the CI effect by having participants learn different patterns of upper-limb movements in a barrier-knockdown task. The goal was to reproduce the appropriate pattern as quickly and accurately as possible upon presentation of an imperative stimulus (e.g., blue light meant pattern A). All three required patterns were allotted the same amount of practice; however the order in which these patterns were practiced differed for the two experimental groups. In one experimental group, individuals practiced in a blocked fashion. This meant that all practice attempts of one pattern were completed before another and so on. The other experimental group practiced in a random fashion, whereby practice attempts of all the different movement patterns were intermixed, but where no more than two trials of the same pattern could be practiced consecutively.

Shea and Morgan (1979) found that in acquisition, individuals that performed in a blocked fashion outperformed those in the random practice group. Specifically, total response times were significantly faster for the blocked group and remained so consistently throughout acquisition. However, the findings were reversed when these same individuals returned for blocked and randomly ordered retention tests. Now it was the random practice group that yielded better response time scores, especially so for the randomly ordered retention trials (which may be thought of as reflecting a more realistic order of how daily living activities and skills are performed). Although blocked performance resulted in short-term advantages in motor performance, random practice, seemingly disadvantageous for short-term performance, was actually more beneficial for long-term gains in motor retention. The results of this study where quite surprising and have since generated considerable research that has attempted to replicate, extend, explain and apply the CI effect (e.g., Albaret & Thon, 1998; Lee & Magill, 1983, 1985; Shea & Zimny 1983, 1988; for reviews, see Brady, 2004; Magill & Hall, 1990).

Since the publication of Shea and Morgan (1979), a number of hypotheses have been put forth to explain this robust effect. The two dominant hypotheses are: 1) the elaborative and distinctive processing hypothesis (Shea & Zimny, 1983, 1988); and 2) the forgetting and reconstruction hypothesis (Lee & Magill, 1983, 1985). Shea and Zimny (1983) suggested that learning in a random fashion results in the use of more variable and multiple processing strategies within working memory. Consequently, this leads to more distinctive and elaborate processing of the material to be learned. Moreover, random practice facilitates more comparative, memorable and meaningful representations of and between the movement tasks being performed. In blocked practice however, less complex processing is required by the learner. Instead, once an action plan has been set forth, it is just repeated more or less automatically from trial to trial. Empirical designs have supported this hypothesis (e.g., Shea & Zimny, 1988; Wright, 1991; Wright, Li, & Whitacre, 1992). For instance, Wright et al. (1992) had individuals learn different motor sequences in a random or blocked fashion, but introduced supplemental intratask, intertask, or no additional processing between practice trials. These authors found that those who practiced in a blocked fashion but engaged in additional intertask processing did better in delayed retention compared to those with no additional processing. Moreover, those who practiced in a random manner did not benefit from the additional intertask processing, but actually did worse than those who practiced in a random fashion without additional processing. These authors suggested that the additional processing in blocked practice was similar to the processing engaged in by individuals in the random practice alone, which brought about gains in delayed retention performance. Interestingly, it seemed that additional processing was unnecessary and even detrimental to the already randomly scheduled practice group.

Lee and Magill (1983, 1988) have proposed an alternative, but not contradictory, explanation. They suggested that in random practice, decay of information related to the previously produced movement trial occurs when the next required trial involves a different task than the task just completed. Specifically, participants would have to abandon processing of the previous task in order to generate a new action plan for the present task. This would result in more frequent calls into long-term memory since individuals would have to partially reconstruct an action plan at the beginning of each trial if practicing in a random fashion. However, blocked practice would result in superficial processing within working memory as the task would remain unchanged over trials. Blocked practice, therefore, would result in facilitated acquisition performance, but would not be beneficial for the processing needed for long-term gains in motor retention and transfer. Empirical evidence has also supported the reconstruction hypothesis (e.g., Lee, Wishart, Cunningham, & Carnahan, 1997). A key factor to the reconstruction hypothesis is the action planning that occurs just prior to each trial during practice. Presumably random practice involves reconstructing action plans at the beginning of every trial, while blocked practice just reinstates the already present action plan from working memory. Cleverly, Lee et al. (1997) added an additional group called the random plus model group. This group was reminded of the motor pattern they needed to produce prior to a given trial via a visual and auditory demonstration of the task, which the authors thought might remove some of the problem-solving activities that are normally associated with random practice. Essentially, the 'solution' was given to participants in this group with the model guiding the learner through the action-planning process, thereby diminishing the reconstruction benefits normally encouraged by random practice. The results were as anticipated; the performance *disadvantage* in acquisition normally associated with random practice was eliminated in this random plus model group as absolute constant error scores were similar to the blocked group throughout acquisition. Furthermore, the learning *advantage* normally evident with random practice was also eliminated with the addition of this modeled information as immediate and delayed retention scores for this group were significantly worse than the random group.

Taken together, what seems to be important and central to both hypotheses is that in order for practice to be effective for motor learning, a certain level of cognitive effort and deeper processing of information needs to occur. Interestingly, some research has suggested that the amount of processing an individual can effectively undertake can change as a function of the nature of the task performed and the individual performing the task (e.g., Albaret & Thon, 1998; Guadagnoli & Lee, 2004). Consequently, this can affect what comprises optimal practice organization for motor learning

Challenges to Contextual Interference

A caveat to the CI effect was demonstrated empirically. Specifically, Albaret and Thon (1998) found evidence that task complexity can modulate the effects of CI. These researchers had participants learn to draw geometrical patterns of two, three, or four line segments in either a blocked or random order. The findings revealed that the typical CI effect was found for those individuals who practiced the two and three segment patterns. Performance in acquisition was superior by those individuals who practiced in a blocked fashion compared to those who practiced in a random fashion, with reverse group performance findings in the delayed retention and transfer tests (i.e., random groups outperformed the blocked groups). Interestingly, the CI effect was not observed in transfer for those individuals who learned the four-segment pattern. Instead, there were no differences in performance scores for the random and blocked groups for this most complex task. Albaret and Thon argued that the task may have been sufficiently complex to make participants rely on more effortful working memory processes in the blocked practice condition, instead of shallow cognitive processes of movement information in working memory which have been tenants of previous hypotheses (e.g., Lee & Magill, 1983, 1985; Shea & Zimny, 1983, 1988). This additional cognitive effort by the blocked group in acquisition resulted, therefore, in beneficial gains in motor transfer performance comparable to the random group, for the most difficult, 4-segment task.

Guadagnoli and Lee (2004) suggested that optimal practice conditions may depend on more than task complexity. Specifically, in their Challenge Point framework, these authors suggested that the effectiveness and usefulness of a practice regime also needs to be considered with respect to the skill level of the participant performing the task. These authors suggested that motor skills not only have a nominal task difficulty (the constant amount of task difficulty, regardless of who is performing the task and under what conditions it is being performed) but also a functional task difficulty. Functional task difficulty refers to "how challenging the task is relative to the skill level of the individual performing the task and to the conditions under which it is being performed" (Guadagnoli & Lee, 2004, p213). Now relating this concept to contextual interference practice schedules in particular, Guadagnoli and Lee suggested that tasks with higher nominal task difficulty may benefit from blocked practice to a greater extent than tasks with lower nominal task difficulty. Conversely, random practice advantages may be greater for tasks of lower nominal task difficulty and lesser for tasks with higher nominal difficulty. Moreover, individuals with lower skill levels may benefit from lower CI levels (i.e., blocked practice), and higher levels of CI (i.e., random practice) would be beneficial for more highly skilled individuals. So, as nominal and functional task difficulty increases, blocked practice may be more appropriate for novice performers than random practice. The Challenge Point framework raises the interesting point that the 'individual' is an integral part of the learning process, and may be an important factor in deciding what practice regime will be optimal. Furthermore, effective practice scheduling may change depending on the individual performing the task.

Effective Practice vs. the Individual

Motor learning research findings attempt to provide practical utility to help improve performance in real life situations. Indeed, many published motor learning papers include a statement that goes something like, "the present findings offer potential application opportunities to sport, educational, and rehabilitation settings". Although the aforementioned empirical findings certainly appear to provide potentially beneficial practice regimens, another factor that is crucially important has, until recently, been completely understudied within the motor learning domain – the individual. Standard motor learning paradigms give the experimenter total control over how practice is organized. This approach ignores a potentially influential factor: namely, whether experimenter-controlled manipulations are actually representative of how participants would organize their own learning experience if given the opportunity. It is true that in the majority of sport, educational, and rehabilitation settings there is involvement of teachers, instructors, and practitioners to varying amounts and for varied periods of time. But the bottom line is they will not be there every step of the way, so how individuals learn, maintain and improve upon a motor skill -- whether it be swinging a golf club or relearning skills of daily living after an injury -- will eventually end up in their own hands. The question then becomes "are the strategies and practice regimes shown to be advantageous within the research setting truly effective and practical for individuals and representative of what the individual would actually do if given the opportunity?"

Although many of the findings of motor learning research have practical application potential, evidence exists that individuals may not agree with, or enjoy, the practice schedules often given to them within experimental designs. For instance, in a distribution of practice study, Baddeley and Longman (1978) taught postal workers a new technology of sorting mail by postal codes in one of four different practice regimes. Some trained in a massed fashion, 2 hours, twice a day over three weeks, while others practiced in a distributed fashion, 1 hour, once a day over 12 weeks[1]. Consistent with the distribution of practice literature (see for a review, Lee & Genovese, 1998), the massed group (2 x 2) was least effective in both training performance and in retention performance conducted several months later. Relevant to present purposes, however, was

[1] Two other experimental groups were also examined, 1 hour twice a day and 2 hours once a day; however, results of the most massed and distributed groups are more interesting and relevant to present discussion. So, these additional groups will not be discussed further. In addition, although amount of time of training was initially designed to be equal for all groups - 60 hrs - only the distributed group performed in this timeframe. The other groups ended up having an additional 20 hrs because performance levels were not as high as initially anticipated.

that at the time of retention Baddeley and Longman also asked participants to answer some subjective rating questions. Participants were asked to rate how satisfactory they felt their training schedule was and which schedule they would prefer to use if trained again. In terms of enjoyment of the training schedules, participants rated the more massed schedule (2 x 2) as most satisfactory and the distributed schedule (1 x 1) as least satisfactory. Moreover, when answering which training schedule they would prefer to follow in the future, a great majority said they would choose the massed schedule, even when they were told the distributed practice group did better overall.

Although studied more extensively in the memory literature (e.g., Dunlosky & Nelson, 1992; Kimball & Metcalfe, 2003; Metcalfe & Shimamura, 1994; Richards & Nelson, 2004), judgments of learning (JOLs) are a recent manipulation within motor learning research (e.g., Dail & Christina, 2004; Simon & Bjork, 2001, 2002). Essentially, participants are asked at different stages of practice to rate their level of confidence or predict future performance on a task if given no more practice on that task. Results of such studies reveal that current level of proficiency can influence JOLs. For instance Simon and Bjork (2001), using a practice schedule design similar to Shea and Morgan (1979) and task modeled after Lee et al. (1997), asked individuals to judge how confident they were after every few trials, by making a numerical estimate regarding how well they expected to perform a given pattern the next day if given no more practice. The result was that individuals in the blocked group were overconfident in their estimates compared to their actual retention performance. On the other hand, the random group was much more accurate in their judgments compared to retention performance. These authors suggested that blocked practice resulted in a false sense of confidence of proficiency for the task because participants were using current performance of the task as their primary basis for predicting future performance. Interestingly, however, the random group was also basing their JOL decisions on current performance. If put in the context of the present discussion, an individual may be discouraged with random practice as quick gains in performance are not often evident when practicing, as was indeed the case in this study as the typical CI effect was observed. A potentially important implication of this is that if given the opportunity to choose their own practice schedules, individuals may choose a schedule more encouraging to them, irrespective if other schedules are more effective.

The key thing that needs to be taken away from these studies is that even if standard results are found (for example a typical CI effect was found in Simon and Bjork's (2001, 2002) studies), when you ask individuals to consider their practice preferences, what an individual finds preferable, enjoys, or finds encouraging about practice can be very different from what has been shown to be effective for motor learning. Given the findings of Baddeley and Longman (1978) and the implications from Simon and Bjork and Dail and Christina, 2004, it is likely that individuals may choose to organize their practice differently than what might be considered "optimal" from a motor learning perspective. This does not imply that individuals will necessarily do what is ineffective, but they may not adopt the same strategies experimenters often impose on them in experimental designs. With this in mind, an important new manipulation within the literature is that of self-regulation. Specifically, recent designs have relinquished certain controls over to the individual and have examined what effect this has on motor skill acquisition, retention, and transfer.

Self-Regulation Manipulations and Motor Learning

Recently within the motor learning domain, self-regulation of various aspects of the learning environment have been investigated, such as augmented feedback (e.g., knowledge of results), model observation, and use of physical devices. Although the number of studies to date is not large, it is continually expanding and consistent results are being revealed.

Janelle and colleagues (Janelle, Kim, & Singer, 1995; Janelle, Barba, Frehlich, Tennant, & Cauraugh, 1997) allowed a group of participants to regulate the augmented feedback received in a complex throwing task. They found that allowing learners to decide when they wanted to receive feedback enhanced the effectiveness of that feedback. The participants who self-regulated their feedback schedule outperformed yoked participants who had no control over the provision of feedback, as indicated by retention performance. Interestingly, learners chose a relatively low feedback frequency (average 7%, Janelle et al., 1995; average 11.5%, Janelle et al., 1997) even though there were no constraints on how much feedback they could receive. The self-regulated feedback schedules also faded with time (i.e., they chose to receive feedback less often as practice progressed). The authors suggested that because participants did not constantly seek external guidance, and still performed the task better than yoked controls, that participants seem to have a relatively good sense of how to learn effectively when provided the opportunity to self-regulate their feedback schedule. Chiviacowsky and

Wulf (2002) also examined the influence of self-regulated feedback in a sequential timing task. Compared to a yoked control group, the self-regulated group learned the task more effectively (based on delayed transfer performance). In a follow-up study using the same task, Chiviacowsky and Wulf (2005) found that when comparing two self-regulated groups, the self-regulated group that was more effective was the one that could ask for feedback *after* a trial was completed compared to the group that could only ask for feedback *prior* to completing a trial. Self-regulated feedback, therefore, seemed to be effective for learning because learners could make a decision about feedback based on their *own* estimation of performance.

Wulf and Toole (1999) have also demonstrated that giving individuals control over the use a physical device to assist in learning a motor skill can have a beneficial effect. Specifically, they taught individuals how to perform a slalom motion on a ski-simulator, and individuals were allowed to choose when they wanted the assistance of ski poles. The participants of one group were allowed to choose when they wanted to use the poles (self-regulated group), and were compared to a yoked group that had no control over their schedule. Even though the self-regulated and yoked groups demonstrated similar performances (movement amplitudes) during practice, allowing learners to self-regulate when they wanted to use the poles was more effective for learning, as shown by performance in a no-pole retention test.

More recently, researchers have demonstrated the effectiveness of self-regulated observational learning for the badminton long serve (Wrisberg & Pein, 2002) and the basketball jump-shot (Wulf, Raupach, & Pfieffer, 2005). In Wulf et al. (2005), novices learned a basketball jump-shot from the free-throw line and were allowed to choose when they wanted to view an expert model on videotape. Consistent with much of the other literature, those individuals that were allowed to choose when to view the videotape yielded better movement form scores in retention when compared to a group of yoked controls. A recent study conducted by Bund and Wiemeyer (2004) demonstrated that when learning a table tennis forehand stroke, those individuals who were free to choose some aspect of their practice regime (either observation of a videotape or variability in practice dimensions (different speeds and directions of the ball)) performed better than yoked controls.

Indeed, increasing evidence suggests that allowing individuals to control different aspects of their learning environment has beneficial effects on motor retention and transfer. The question becomes, what effect does self-regulated *practice scheduling* have on motor learning?

Self-Regulated Practice Schedules and Motor Learning

Although most of the literature describing the effects of self-regulated practice conditions has been concerned with verbal or cognitive learning, there is growing evidence for the effectiveness of self-regulated practice schedules in the motor learning domain. Titzer, Shea, and Romack (1993) examined the effects of a self-regulated practice schedule on a computer-based barrier knockdown task, which required particpants to strike barriers in a particular sequence as quickly as possible. The typical CI effect was demonstrated in blocked and random groups; however, these authors found that learners who could self-regulate their practice order performed equivalent to the blocked group during acquisition and also equivalent to the random group during retention. Moreover, both the self-regulated and random groups made fewer errors than the blocked practice group in retention. A limitation to this study however, was the lack of a yoked control group for the self-regulated group. Specifically, in the absence of a yoked control group there is no evidence that the beneficial results of self-regulation occurred from the ability to self-regulate practice in general or because of the actual practice schedules adopted by these individuals. More recent studies by Wu and Magill (2004, 2005) revealed that a self-regulated schedule was superior to yoked-control groups when required to perform golf putts from various distances (2004) or when required to learn different key-press sequences (2005). This finding lends further support to the notion that a participant's control over the practice schedule can have a positive influence on retention performance, even when the exact nature of the schedule is the same.

Notwithstanding, examining self-regulated practice scheduling is relatively new in the motor domain (e.g., these studies have only been published as abstracts from conference proceedings), so there is obviously room and a need for paradigms of this kind to be explored and extended. Specifically, given that: (a) how practice is organized affects how motor skills are learned (see Magill & Hall, 1990); (b) how an individual would prefer to practice may be different than what is often administered (e.g., Baddeley & Longman, 1978); (c) the complexity of the task engaged in has been shown to interact with practice variables often employed in motor learning research (e.g., Albaret & Thon, 1998; Guadagnoli & Lee, 2004); and (d) self-regulation, and in particular self-regulated practice scheduling, has been demonstrated to enhance motor learning (e.g., Chiviacowsky & Wulf, 2002, 2005; Janelle et al., 1995, 1997; Wu & Magill, 2004, 2005; Wulf and colleagues, 1999, 2005), then examining how individuals self-regulate as a function of task complexity seems a logical next step to gain a better understanding of how self-regulated practice influences motor learning.

In cognitive psychology, there is evidence to suggest that how an individual chooses to self-regulate their practice changes based on one's perceived difficulty of the task. For example, Son (2004) required individuals to learn word-pair associations and demonstrated that when given the opportunity to choose their own practice order, individuals did so based on self-judgments of task complexity. Specifically, individuals were instructed that once a word-pairing was presented to them, they could either have the same pairing presented to them again on the next trial, or could choose to study that pairing again later in practice. What resulted was that word-pairings that were judged to be easy were chosen to be practiced later (in a more spaced fashion), whereas those word pairings judged to be more difficult were practiced earlier (in a more massed fashion). To date, no study within the motor skills domain has looked at self-regulated practice as a function of task complexity. Based on the finding by Son (2004) and from what we know about current motor learning literature (e.g., Albaret &Thon, 1998), it seems reasonable and important to investigate how self-scheduled practice may be impacted by task complexity.

Consequently, the aim of the present study was twofold. The first aim was to examine how self-regulation impacts performance during the learning process, primarily by giving participants control over the organization of their practice schedule, and comparing their performance to yoked control groups and standard experimenter-prescribed schedules (random and blocked). The second aim was to assess how self-regulated strategies change as a function of task complexity and to investigate these effects on motor acquisition, retention, and transfer. Based on previous literature, it is hypothesized that self-regulation will once again be shown to be advantageous for motor learning, particularly so for retention and transfer. It is also hypothesized that self-regulated strategies will change as a function of task complexity. Specifically, following the lead of Son (2004) it is anticipated that individuals will switch between motor tasks less frequently in practice when the tasks are deemed to be hard, and more frequently when the tasks are easy. In terms of the collective performance of all groups, it is hypothesized that when the task is more difficult, blocking practice to a greater extent may not be detrimental for retention of the motor skills (see Guadagnoli & Lee, 2004) but that typical CI effects are anticipated for the less difficult tasks. It is hoped that through utilizing self-regulated groups, as well as appropriate control groups on tasks of differing complexity, that a deeper understanding of the influence of self-regulation on the acquisition and retention of motor skills will be attained.

Method

Participants

Ninety-six undergraduate students (age range 18-28 years) from the McMaster University community participated in this study. Participants were assigned to one of eight different groups (n=12), which differed in terms of the difficulty of the tasks performed (easy vs. hard) and the practice schedule utilized (e.g., blocked, random, self-regulated, yoked to self-regulated). Assignment to groups was randomized with the exception that gender within each group remained approximately equivalent. All participants had normal or corrected-to-normal vision and were right handed with the exception of one left handed participant in each group. The study was approved by and conducted in accordance with the ethical guidelines of McMaster University Research Ethics Board. Participants were naïve to the purpose of the study, gave informed consent prior to the experiment, and received $10 in compensation.

Apparatus and Task

Individuals sat in front of a computer monitor with a keyboard and Microsoft 2-button laser mouse device with pad on a standard tabletop. Individuals were required to perform an aiming movement which consisted of manoeuvring the mouse cursor through a pattern of squares displayed on the computer screen. Each pattern consisted of five squares which were imbedded within a grid of differently arranged black and white squares on a blue background (see Figure 1). The path of the pattern within the grid was denoted by red lines attaching adjacent squares. Simultaneous with the cursor movement, individuals were required to pause in each square long enough to depress the mouse button that was appropriate for the colour of the square. A white square required a left mouse button press and a black square required a right mouse button press. The goal was to complete the pattern as fast as possible without making errors.

Figure 1 illustrates variations of the visual array that was presented to participants on the computer monitor. The movement path within the grid of 16 squares remained consistent between patterns; however, there were 4 patterns to be learned which differed in terms of the sequencing of white and black squares within each pattern. The specific sequencing of right and left mouse keys made each pattern more or less difficult to complete quickly and without making errors. The set of grids in the top half of Figure 1 illustrates patterns that were less difficult to perform, and the bottom half of Figure 1 illustrates patterns that were more difficult to perform. In addition, the easy patterns were completed with individuals using their dominant mouse hand and the hard patterns were completed with individuals using their non-dominant mouse hand. Therefore, the arrangement of the grid of black and white squares, coupled with the limb used to perform the patterns, determined the overall task difficulty of the set of patterns to be learned by each group.

The software tool, E-Prime®, version 1.0, initiated all stimulus displays and recorded all dependent measures of interest.

Procedure

All participants in each group performed 128 practice trials of the four patterns to be learned (32 trials per pattern). The primary difference between groups was the schedule used to practice the set of patterns: blocked, random, self-regulated, and yoked-to-self-regulated (hereafter called "yoked"). The blocked group practiced all 32 acquisition trials of one pattern before any trials of another were completed. The random group's practice schedule was ordered in blocks of 16 trials, with four trials of each pattern ordered such that no more than two trials of any pattern were practiced consecutively (cf. Shea & Morgan, 1979). The self-regulated group practiced the patterns in the order of their choosing[2]. Participants in the yoked group were gender-matched to each of the participants in the self-regulated group and practiced the patterns in an identical order as their self-regulated match. However, since they did not choose their own practice order, the yoked group served as a control group that had an identical practice order as the self-regulated group that was not subjectively determined.

At the beginning of the first session (the "acquisition" phase), individuals were shown a series of instructional screens that described the task, including all of the different patterns, which the individuals were allowed to study for 30 seconds. Included in this information was a description of the feedback that was provided to them after every trial. This feedback consisted of three pieces of information: 1) movement time (MT) for the trial, 2) pattern accuracy (i.e., were the correct mouse buttons pressed in the correct order?), and 3) cursor accuracy (i.e., was the mouse cursor inside the square when the button press was made?). This feedback screen was displayed for 5 seconds during the protocol. Subsequent to this screen, an additional screen was displayed which informed individuals about how many trials remained for each pattern. In addition to the

2 Initial pilot study results revealed that self-regulated participants tended to always follow an "ABCD" ordering. Specifically, most individuals tended to start with Pattern A. Here, the pattern designation was changed across participants such that Pattern A was sometimes called Pattern B, or C, or D. The specific assignment of letter designation to each pattern was completely counterbalanced across individuals within each of the groups according to a Williams square design.

information regarding the number of trials remaining, the self-regulated group also were presented with the question "which pattern would you like to practice on the next trial?; Pattern A = press a, Pattern B = press b....". The keyboard button they pressed determined which pattern was practiced on the next trial[3].

A trial started with a screen that displayed the pattern that would be practiced during that trial (e.g., Ready, Pattern A). Following a 2-s exposure to this screen, individuals were required to place a mouse cursor into an initially-red starting square at the bottom left corner of the grid. This starting position square was always in the same location as the first square in each actual pattern. Therefore, when the pattern display grid appeared, participants already had the mouse cursor positioned within the first square of the sequence. After a 1 second homing period in the red starting square, a tone sounded and the pattern display grid for that trial appeared. Participants were instructed that they did not need to start their movement right away, but rather, to begin the trial whenever they felt ready to complete the entire movement quickly and accurately. After their movement was completed, individuals viewed the feedback and trial-attempts-left screens as described previously after every trial.

Individuals completed two sessions. The first experimental session, the "acquisition" phase, consisted of 128 practice trials in which participants were required to complete 32 trials of each pattern in their group defined orders. (Note that although the individuals in the self-regulated condition chose their practice order, there was still experimental control as to how much practice was allowed for each pattern; 32 trials per

[3] The Blocked, Random, and Yoked groups hit the space bar to advance to the next trial.

pattern). The second session, the "retention and transfer" phase, consisted of four trials of each previously practiced pattern in a random order with no augmented feedback. Following this retention test the participants completed a transfer block which consisted of a new (i.e., previously unpracticed) pattern performed in four trials with both the dominant and non-dominant hands (see Figure 1). The ordering of these transfer trials was counterbalanced across participants using an ABBABAAB or BAABABBA order (where A = dominant hand and B = non-dominant hand). This transfer test is particularly interesting because the transfer pattern and procedures were identical for all eight groups, regardless of whether the groups had practiced the easy or hard tasks in acquisition. The acquisition and retention/transfer sessions were separated by 24 hr.

Dependent Measures

MT, Planning time (PT), Pattern Errors, and Cursor Errors data were collected on each trial. MT was the main measure of interest and was recorded as the time from when individuals pressed the first button in the first square until they had pressed the final button of the pattern in the last square. PT was recorded as the time of stimulus display onset until the first button press had occurred (see Figure 2). Each temporal measure was recorded and reported in ms. Pattern errors referred to incorrect button presses during the sequence (e.g., left mouse button when they should have hit the right mouse button). Cursor errors referred to a button press that occurred when the cursor was outside the appropriate square in the pattern. As each pattern consisted of five squares, up to 5 pattern and 5 cursor errors could occur during each trial. Errors occurring within a trial of both pattern and cursor were tallied with a score of 1 or a score of 0 if an action was correct and were summed out of 5 (maximum) for each trial, respectively. Error scores were then summed out of 20 (5 potential x 4 trials in a block per pattern).

The number of switches that occurred during acquisition was also recorded. A switch occurred whenever different patterns were performed on two consecutive trials during the practice phase (e.g., pattern A was performed on Trial 1 and pattern C on Trial 2).

Data Analysis

Switch Data. Switch data for the Self-Regulated groups were initially submitted to a 2 Task Complexity by 8 Block[4] mixed analysis of variance (ANOVA) with block as a repeated measure. This analysis was conducted to assess how switch frequency changed as a function of Task Complexity. To further examine how the switch patterns of the Self-Regulated groups changed over acquisition, the switch data were also submitted to a 2 Task Complexity by 2 Switch Frequency (Switch Rarely, Switch Often) by 8 Block mixed ANOVA with the last factor as a repeated measure. Switch frequency subgroup divisions were determined based on pilot study results. Specifically, in a pilot study, individuals who chose to switch 'rarely' did so on average for less than 25% of the trials. Therefore, for present purposes, inclusion in the switch rarely group and switch often group were pre-determined to be switching less than 25% of the trials and switching greater than 25% of the trials, respectively.

Acquisition. Acquisition data for MT, PT, Pattern Errors and Cursor Errors were analyzed using a 2 Task Complexity (Easy, Hard) by 4 Group (Blocked, Random, Self-

---

[4] A block consisted of 16 trials.

Regulated, Yoked) by 4 Pattern (A, B, C, D) by 8 Block (16 trials; 4 trials of each pattern) mixed ANOVA where pattern and block were treated as repeated measures.

Retention. Retention data for each dependent measure were analyzed using a 2 Task Complexity (Easy, Hard) by 4 Group (Blocked, Random, Self-Regulated, Yoked) by 4 Pattern (A, B, C, D) by 2 Block (Last Acquisition block, Retention block) mixed ANOVA where pattern and block were treated as repeated measures.

Transfer. Transfer data for each dependent measure were analyzed using a 2 Task Complexity (Easy, Hard) by 4 Group (Blocked, Random, Self-Regulated, Yoked) by 2 Hand (Dominant, Non-Dominant) mixed ANOVA where hand was the repeated measure.

Preliminary analyses of the temporal dependent measures revealed some large departures from homogeneity of variance, particularly so when comparing the performance of easy versus hard patterns. Therefore, a natural logarithm transform was performed on the temporal data (MT, PT) prior to statistical analyses. All significant effects and interactions were examined using Tukey's post hoc procedures where appropriate with α set at $p < 0.05$.[5]

[5] All main effects of Pattern and interactions with Pattern that do not include Task Complexity as a factor are meaningless, and will not be reported. That is, Pattern A for the easy task and Pattern A for the hard task are not directly related (i.e., Pattern A of the easy task is no more related to Pattern A for the hard task than it is to B, C, or D).

Results

Switch Data Comparison

Random vs. Blocked vs. Self-Regulated

There were differences in the number of switches that occurred between groups. Specifically, on average the Random group switched 13.5 times per block of 16 trials for the easy tasks and 13.6 times per block for the hard tasks. No switches occurred, of course, for the Blocked groups. The Self-Regulated groups switched an intermediate amount compared to the Random and Blocked groups and the following analyses where conducted to examine the different self-regulation switch strategies used during acquisition by these groups as a function of task complexity.

Self-Regulation vs. Task Complexity

An additional analysis was performed specifically looking at differences in number of switches between the two Self-Regulated Groups over acquisition as a function of Task Complexity. This analysis revealed a main effect of Block, $F(7,154)=2.14$, $p<.04$, whereby block 8 had significantly more switches than block 4. Although the main effect of Task Complexity and the interaction of Task Complexity and Block did not reach conventional levels of significance ($p=0.52$ and $p=0.42$, respectively), those individuals performing the hard tasks maintained a relatively consistent switch pattern across all blocks of acquisition, whereas those who practiced the easy tasks tended to switch more often early (blocks 1 and 2) and late (blocks 7 and 8) in acquisition (see Figure 3).

Self-Regulation vs. Switch Frequency vs. Task Complexity

This analysis investigated how the switch patterns within Self-Regulated groups changed as a function of task complexity (see Table 1). This analysis revealed main effects of Switch Frequency, $F(1,20)=60.64, p<.01$, and Block, $F(7,140)=2.47, p<.02$, as well as a significant interaction of Task Complexity, Switch Frequency, and Block, $F(7,140)=3.40, p<.01$. As expected, those participants who switched rarely did so significantly less than those who switched often. Participants switched significantly less frequently on block 4 compared to block 8. Post hoc analysis of the interaction revealed that there was no difference in number of switches between those who switched rarely for each of the task complexities. However, of the participants who switched frequently, those who practiced the easy tasks switched significantly more often on blocks 1, 7 and 8 compared to those participants who practiced the hard tasks (see Figure 4).

Acquisition and Retention

Movement Time (MT)

Acquisition. This analysis revealed main effects for Task Complexity, $F(1,88)=208.64, p<.01$, and Block, $F(7,616)=216.43, p<0.01$. Participants who practiced the easy tasks (1005 ms) moved significantly faster than participants who practiced the hard tasks (1820 ms). Participants improved MT performance over acquisition, with reductions in MT no longer significant by block 6, although continually decreasing even into block 8.

There were also significant interactions of Task Complexity and Group, $F(3,88)=4.63, p<.01$, Task Complexity and Pattern, $F(3,264)=4.20, p<.01$, Task

Complexity and Block, $F(7,616)=2.70, p<.01$, as well as Group and Block, $F(21,616)=4.67, p<.01$. Post hoc analyses revealed that for the easy tasks, the Self-Regulated group (1112 ms) was significantly slower than the Yoked group (869 ms), with the Random (978 ms) and Blocked (1060) groups' performance intermediate but not significantly different from each other or the other groups. In regard to the hard tasks, the Blocked group (1565 ms) was significantly faster than both the Self-Regulated (1911 ms) and Yoked (1914 ms) groups, which were not statistically different from each other or the Random group (1889 ms). Participants who practiced the easy tasks were significantly faster at completing pattern C compared to other tasks, however, there were no MT differences between patterns for those who practiced the hard tasks. Looking at performance across acquisition between tasks of varying complexity; continued improvement was evident for both the easy and hard tasks. However, reduction in MTs were no longer significant for those who practiced the easy tasks after block 5, whereas no further significant reductions in MT occurred after block 6 for those who practiced the hard tasks. As is seen in Figure 5, post hoc analysis of the Group by Block interaction revealed that in block 1, the Blocked group overall was significantly faster than the other groups; the Random group was significantly slower than the rest of the groups; and performance of the Self-Regulated and Yoked groups fell intermediate and were not significantly different from each other. In block 2, the Self-Regulated and Random groups were not significantly different from each other but were significantly slower than the Yoked and Blocked groups, which were not significantly different from each other. In blocks 3 to 8, the Self-Regulated group was significantly slower than the other groups, which were not significantly different from each other. The Task Complexity by Group by Block interaction approached conventional levels of significance, p=0.08. The trend followed the lower-order interaction of Task Complexity and Group. Specifically, of those participants who practiced the easy tasks, the Yoked group had consistently faster MTs and the Self-Regulated group slower MTs, with the Random and Blocked groups intermediate, with the exception of block 1 where MTs were similar between groups. For those who practiced the hard tasks, the Blocked group appeared to consistently have faster MTs compared to the other groups across all blocks of acquisition (see Table 2a/b and Figure 6). No other effects or interactions were significant.

Retention. This analysis revealed main effects for Task Complexity, $F(1,88)=193.77, p<.01$, and Block, $F(1,88)=29.81, p<.01$. Participants who practiced the easy tasks remained significantly faster in retention compared to those who practiced the hard tasks, and MTs increased in retention compared to the last block of acquisition overall. There were also significant interactions between Task Complexity and Group, $F(3,88)=4.60, p<.05$, Task Complexity and Pattern, $F(3,264)=5.35, p<.01$, as well as a significant interaction of Group and Block, $F(3,88)=18.19, p<.01$. Post hoc analysis of these interactions revealed that for those who practiced the easy tasks, the Blocked group (1046 ms) was significantly slower than the Yoked group (801 ms), while the Random (900 ms) and Self-Regulated (959 ms) groups fell intermediate but were not significantly different from each other or the other groups. There were no significant group differences in MT retention performance for those who practiced the hard tasks (Blocked

= 1503 ms; Random = 1704 ms; Self-Regulated = 1742 ms; Yoked = 1799 ms) (see Figure 7).

Consistent with acquisition performance, pattern C remained fastest amongst the easy tasks, while there were no pattern MT differences for the hard tasks. Most interesting was the interaction of Group and Block (see Figure 8). Post hoc analysis of this interaction revealed that the Blocked, Random and Yoked groups all significantly increased MT performance from the last block of acquisition to retention, however, the Self-Regulated group significantly decreased MT in retention compared to the last block of acquisition performance. In addition, although performance in the last block of acquisition revealed that the Self-Regulated group had significantly slower MTs than all the other groups, which were not different from each other; in retention, the Self-Regulated group had the fastest MTs and specifically were significantly faster than the Blocked group, with the Random and Yoked falling intermediate but not significantly different from each other or the other groups. No other effects or interactions were significant.

Planning Time (PT)

Acquisition. This analysis of PT yielded main effects for Group, $F(3,88)=3.22$, $p<.03$, and Block, $F(7,616)=107.21$, $p<0.01$. Participants in the Blocked groups (622 ms) spent significantly less PT compared to the Random (933 ms), Self-Regulated (942 ms), and Yoked (916 ms) groups. As well, there was a significant decrease in PT as practice increased, with reductions in PT no longer significant after block 5.

There was also a significant interaction between Group and Block, $F(21,616)=1.72$, $p<.02$. Post hoc analysis of this interaction indicated that there were no significant PT differences between groups on block 1. However the Blocked group spent significantly less PT than the other groups for blocks 2 through 8. In general, the Random, Self-regulated, and Yoked groups did not differ in planning time across acquisition, with the exception that on blocks 2 and 4, the Yoked group spent significantly less time planning compared to the Random group (see Table 2a/b and left side of Figure 9). No other effects or interactions were significant.

Retention. This analysis revealed a main effect for Block, $F(1,88)=84.86$, $p<.001$, whereby more PT was spent in retention compared to the last block of acquisition. There was also a significant interaction of Group and Block, $F(3,88)=4.29$, $p<.01$. Post hoc analysis of this interaction indicated that all groups increased PT in retention compared to the last block of acquisition (see Table 2a/b and right side of Figure 9). However, the Blocked group increased their PT to the greatest extent from the last block of acquisition to retention (see Figure 10). All other effects and interactions were not significant.

Pattern Errors

Acquisition. This analysis yielded main effects of Task Complexity, $F(1,88)=6.84$, $p<.01$, and Block, $F(7,616)=4.89$, $p<.01$. Participants who practiced the easy tasks had made fewer pattern errors during acquisition compared to those who practiced the hard tasks. Moreover, participants made significantly more errors on block 1 compared to the other acquisition blocks, which were not different from each other. There was also a significant interaction of Task Complexity and Pattern, $F(3,264)=3.17$,

$p<.02$. Post hoc analysis of this interaction indicated that for the easy tasks there were no significant differences for error scores between patterns; however, for the hard tasks, pattern C was performed with less error than patterns A and D, which were not different from each other. Pattern B was intermediate and not significantly different from the other tasks. No other effects or interactions were significant (see Table 2a/b). Particularly noteworthy was the lack of significant effects or interactions involving Group.

Retention. This analysis revealed a main effect of Block, $F(1,88)=7.52, p<.01$, whereby significantly more pattern errors were made during retention compared to the last block of acquisition. No other effects or interactions were significant (see Table 2a/b).

Cursor Errors

Acquisition. Analysis of cursor error data revealed main effects of Task Complexity, $F(1,88)=7.34, p<.01$, and Block, $F(7,616)=9.50, p<.01$. Participants who practiced the hard tasks committed more cursor errors than those who practiced the easy tasks. More cursor errors were committed in blocks 7-8 compared to blocks 1-5. There were also significant interactions between Task Complexity and Group, $F(3,88)=3.07$, $p<.03$, Group and Block, $F(21,616)=2.28, p<.01$, as well as Task Complexity, Group, and Block, $F(21,616)=1.58, p<.05$. Post hoc analysis of the superseding interaction indicated that there were no differences in cursor error scores between groups that practiced the easy tasks, with the exception that on block 8, the Self-Regulated group made more errors than the Blocked group. When looking at hard task performance, however, group differences were apparent throughout acquisition. Specifically, in block 1, the Blocked and Self-Regulated groups made more errors than the Random group, and the Blocked group also made more errors than the Yoked group. On blocks 3, 4, and 7 the Blocked group made significantly more errors than the other groups. Cursor error scores were not significantly different between the Blocked and Self-Regulated groups, or the Random and Yoked groups, on blocks 6-8, although the Blocked and Self-Regulated groups made more errors than the Random and Yoked groups on blocks 6 and 8 (see Table 2a/b and Figure 11). No other effects or interactions were significant.

Retention. This analysis revealed a main effect of Block, $F(1,88)=4.12$, $p<.04$, whereby more errors were made on the last block of acquisition compared to retention. There were also significant interactions of Task Complexity and Group, $F(3,88)=3.40$, $p<.02$, and Group and Block, $F(3,88)=5.29$, $p<.01$. Post hoc analysis of the Task Complexity by Group interaction indicated that there was no difference in cursor error rates between the groups who performed the easy tasks; however, the Blocked group committed more cursor errors than the Yoked group when the hard tasks were performed, with the Random and Self-Regulated groups intermediate and not significantly different from each other or the other groups. Cursor errors for the Blocked, Random, and Yoked groups remained consistent from the last block of acquisition to retention; however, the Self-Regulated group significantly decreased cursor error rates in retention. Furthermore, this trend was apparent in retention for both task complexities (see Table 2a/b and Figure 12).

Transfer Performance

Participants in all groups of both task complexities completed the same transfer task, which offered an opportunity to explore differences in a common transfer task as a function of the nature of acquisition (i.e., the four groups who had practiced the easy patterns in acquisition had used the dominant hand, whereas the groups practicing the hard patterns had used the non-dominant hand). The transfer task consisted of a new unpracticed pattern with four trials each performed with the dominant and non-dominant hands.

Movement Time (MT)

This analysis revealed a main effect for Hand, $F(1,88)=235.45$, $p<.01$, whereby dominant hand MT (1757 ms) was faster than the non-dominant hand MT (2405 ms). There was also a significant interaction of Task Complexity and Hand, $F(1,88)=104.23$, $p<.01$. Participants who practiced the hard tasks in acquisition performed similarly with both hands in transfer, while those individuals who practiced the easy tasks in acquisition performed significantly and markedly faster with their dominant hand compared to their non-dominant hand in transfer (see Figure 13). The Group by Hand interaction was very close to conventional levels of significance ($p=0.053$). This trend indicated that although all groups had faster MTs with their dominant hand compared to the non-dominant hand, the Blocked and Yoked groups showed greater MT differences between dominant and non-dominant hand performance. No other effects or interactions were significant (see Table 2a/b).

Planning Time (PT)

This analysis yielded a main effect for Hand, $F(1,88)=9.68$, $p<.01$ – participants spent more PT when required to use their non-dominant hand (1456 ms) compared to their dominant hand (1298 ms). There was also a significant interaction of Task Complexity and Hand, $F(1,88)=6.87$, $p<.01$. Participants who practiced the easy tasks spent significantly more PT for movements with their non-dominant hand compared to their dominant hand. However, PT in transfer was not significantly different between hands for those participants who practiced the hard tasks. No other effects or interactions were significant (see Table 2a/b).

Pattern Errors

Results of this analysis revealed only a main effect of Hand, $F(1,88)=4.26$, $p<.04$, whereby significantly fewer pattern errors were committed with the non-dominant hand compared to the dominant hand in transfer. No other effects or interactions were significant (see Table 2a/b).

Cursor Errors

This cursor error analysis revealed only a main effect of Hand, $F(1,88)=13.98$, $p<.01$, whereby significantly more cursor errors were made with the non-dominant hand than the dominant hand in transfer. No other effects or interactions were significant (see Table 2a/b).

Discussion

The experiment reported here was designed to examine the effects of self-regulated practice schedules on motor learning as a function of task complexity. It was hypothesized that self-regulation would reveal beneficial effects during acquisition, but most importantly for retention and transfer. Following the lead of Son (2004), it was also hypothesized that self-regulation strategies might change as a function of task complexity; specifically, less frequent switching was expected for the set of more difficult tasks compared to the easier tasks. Moreover, it was hypothesized that a typical CI effect would be demonstrated between the blocked and random groups for the easy task, but that blocking practice may not be detrimental to retention performance for the more difficult task based on the Challenge Point framework (Guadagnoli & Lee, 2004). Most of the hypotheses were supported by the results of this study.

Effects of Self-Regulation

The results of the present experiment were consistent with previous findings (e.g.,Titzer et al., 1993; Wu & Magill, 2004, 2005) showing that allowing individuals to self-regulate their practice schedules enhanced motor learning. Specifically, individuals in the self-regulated groups showed continued improvement in MT and cursor accuracy performance in a 24-hr delay retention test. This beneficial improvement from the practice trials into retention contrasted sharply to the blocked, random, and yoked groups, all which showed decrements in motor performance in retention. The benefits of self-regulation were not evident, however, until retention, as performance of the self-regulated groups was actually inferior to the other groups in acquisition. This finding is not contradictory to many previous self-regulation studies, however (e.g., Janelle et al., 1995, 1997; Wulf and colleagues, 1999; 2005). Although there were no significant group differences in transfer performance, the self-regulated groups showed better performance in general between both hands compared to the blocked and yoked groups, again suggesting benefits of self-regulation to motor learning compared to other practice schedules.

Effects of Task Difficulty on Self-Regulation Strategies

Interestingly, the beneficial effects of self-regulation emerged irrespective of the different strategies adopted for tasks of differing complexity. Those who practiced the easy tasks switched more frequently during practice than those individuals who practiced the hard tasks. This was most readily apparent when individuals were divided into switch frequency subgroups. Specifically, there were no differences in the number of switches between patterns for those who switched rarely, irrespective of task complexity. However, for those who chose to switch more frequently, members of the self-regulation group who practiced the easy tasks switched more often early and late in practice compared to those who practiced the hard tasks.

This last finding raises an interesting question. It is apparent that there were a number of different strategies adopted by individuals within each of the self-regulated groups for both task complexities. And yet, self-regulation in general was found to be beneficial for motor learning regardless of the strategy. The amount of switching for the self-regulated groups fell intermediate to the blocked and random groups on the average. However, some individuals in the self-regulated groups chose to switch more often while others chose to switch less often. So the question becomes then, did the beneficial effects of the self-regulated groups occur specifically because of the performance of one of the switch frequency subgroups? Specifically, perhaps it was those individuals that switched more frequently in the self-regulated groups that brought about the superior performance of the self-regulated group in general. In this case, these self-regulated individuals could be considered more similar to a random practice schedule. Therefore, poor acquisition performance, but improvements in retention would be in line with typical CI effect literature. Moreover, performance benefits might change as a function of task complexity. Perhaps those who switched more frequently in the easy tasks contributed to the beneficial effects of self-regulation, but those who switched less frequently in the hard tasks yielded the better scores in retention, which would be in line with hypotheses of the Challenge Point framework (Guadagnoli & Lee, 2004). However, if there were no differences in performance within the self-regulated groups using different switch strategies (i.e., switching more or less frequently) or between task complexities, this would suggest that it was not solely the amount of switching that yielded beneficial motor learning effects in the self-regulated groups.

To examine these possibilities I conducted an analysis of the self-regulated group's performance in acquisition and retention as a function of task complexity using a 2 Task Complexity (Easy, Hard) x 2 Switch Frequency (Switch Rarely, Switch Often) x 4 Pattern x 8 Block mixed ANOVA in acquisition (2 Blocks in retention), with pattern and block treated as repeated measures. Planning time and pattern error analyses revealed no significant effects or interactions with Task Complexity or Switch Frequency subgroup and so will not be discussed further. The MT data analysis revealed main effects of Task Complexity, $F(1,20)=45.40, p<.01$, and Block, $F(7,140)=34.94, p<.01$, in acquisition but no effects or interactions with the Switch Frequency factor. Therefore, there were no differences in acquisition in MT performance between those who switched frequently and those who switched less frequently. Retention data analysis revealed main effects of Task Complexity, $F(1,20)=53.15, p<.01$, and Block, $F(1,20)=10.71, p<.01$, with no significant effects involving Switch Frequency. Analysis of cursor errors did reveal a significant Task Complexity by Switch Frequency by Block interaction, $F(7,140)=3.19$, $p<.01$ in acquisition. Post hoc analysis revealed that there were no differences between switch frequency subgroups for those who practiced the easy tasks, however, for those who practiced the hard tasks, the individuals that chose to switch more frequently made fewer cursor errors on block 3 and more errors on block 6 than those who chose to switch less frequently. There were, however, no significant effects or interactions with Switch Frequency subgroup or Task Complexity in retention.

Overall, these additional analyses indicated that the beneficial effect of self-regulation in learning is not due to the number of switches between patterns during practice. Combined with the finding that the beneficial effects of self-regulation shown in retention occurred in both self-regulated groups irrespective of the level of complexity of performance and the switch strategy utilized, these collective results suggest that the self-regulation advantage may be due to benefits afforded by having a certain amount of control of your learning environment.

Effects of Task Difficulty on Groups and CI effect

Another aim of this study was to investigate how all group performances were influenced by task complexity. Task complexity did have differential effects on group performance in acquisition and retention. In acquisition specifically, when the easy tasks were performed, performance of all groups was similar, with only the self-regulated group being significantly slower than the yoked group. Perhaps the easy tasks in general were too simple to elicit differences in performance of the groups, with the exception of the self-regulated group who may have generated more cognitive effort during acquisition with having to continually and actively make decisions about their practice structure. Conversely, the other groups may have employed less cognitive effort associated with performance of these easy tasks as these individuals just had to follow the practice schedule given to them and so may have been less cognitively engaged in acquisition. When the hard tasks were practiced, on the other hand, the Blocked group performed significantly faster than the other groups, which performed similarly to each other. Blocked practice superiority in acquisition is not surprising, as this is a tenant of the traditional CI effect. It should be noted, however, that cursor error scores were higher for this blocked group in acquisition, so some speed-accuracy trade-offs could be contributing to this result.

More interestingly, task complexity also had a differential effect on group performance in retention. Specifically, of those who practiced the easy tasks, the Blocked group was slower than the other groups. This finding is consistent with the CI effect and previous findings involving self-regulated practice (e.g., Titzer et al., 1993).

There were no significant group differences in MT retention performance for those who practiced the hard tasks, although the self-regulated group did significantly decrease MT in retention compared to the other groups. The lack of difference between the Blocked and Random groups, in particular, for the hard tasks is consistent with predictions made by the Challenge Point framework (Guadagnoli & Lee, 2004), suggesting that blocked practice may be more beneficial for motor learning if the task is sufficiently complex enough to cognitively challenge the individual during the learning process. Indeed, the Blocked group that practiced the hard tasks actually maintained the fastest MT performance overall in retention, with accuracy similar across groups. This finding is in contrast to typical CI literature, and reveals that optimal practice scheduling should be based on more factors such as the characteristics of the task (e.g., complexity) as well as the individual performing the task as suggested in the Challenge Point framework. Indeed, the added finding that different schedules (i.e., switching frequently vs. switching less frequently) yielded the same result (i.e., increasing motor learning) in the self-regulated groups indicates that the individual is an integral component of the learning process and taken together, practice schedules could and should be organized to optimize motor learning on an individual to individual basis. Therefore, the predictions laid out by the Challenge Point framework, in conjunction with self-regulation manipulations, merit further research.

Pre-Response Planning

In this design individuals were allowed to take as much time as they wanted to plan their action prior to movement initiation. Although it can not be said for certain what individuals were doing during this time, I suggest that planning time was used by participants to implement various cognitive activities such as: verifying which pattern was required, recalling this pattern from long-term memory stores, as well as rehearsing the pattern before movement execution. The finding in this study that the Blocked group spent significantly less time planning before movement while the other groups spent greater but comparable planning times supports such a conjecture. Individuals in the Blocked groups knew what pattern was required of them on any given trial because there was no trial to trial variation. These individuals would need only to reproduce the current pattern from working memory, and could rehearse the pattern continually because of the predictability of their practice schedule. The Yoked and Random groups would have had a level of unpredictability to their practice schedules, and so would presumably need more planning time to verify, remember, and rehearse the given pattern on every trial. The Self-Regulated groups would have been aware of which pattern would be coming (because they would be the ones choosing it) but could have taken more time to plan and develop strategies for their entire movement in a deeper fashion. For instance, beyond just rehearsing the pattern, perhaps these individuals were also being strategic about the positioning of the mouse cursor in the squares along the sequence to achieve an optimal spatial-temporal relationship. In the future, added manipulations should examine explicitly what pre-response times represent to motor learning, particularly in self-regulation studies.

Interlimb Transfer of Training Effect

The common transfer task administered to all participants offered an opportunity to explore the combined and interactive effects of practice scheduling and task difficulty. Those individuals who practiced the easy tasks in acquisition did so with their dominant hand, whereas those who practiced the hard tasks did so with their non-dominant hand. The transfer task required individuals to perform some trials on a new pattern with both their dominant and non-dominant hands. Although no group differences were revealed for any dependent measures, there was an interlimb transfer of training effect (see Elliott, 1985; Edwards & Elliott, 1987; Taylor & Heilman, 1980). Participants who practiced the easy tasks (with their right hand) in acquisition performed markedly faster with their dominant hand compared to their non-dominant hand in transfer (i.e., there were large differences between the hands). However, performance of those who had practiced the hard tasks (with their left hand) performed similarly with both hands in transfer (i.e., both hands performed equally well). Asymmetric interlimb transfer-of-training effects for sequential movements are said to occur because both hemispheres are involved in left-hand training performance of a sequential movement task whereas during right-hand performance, only the left hemisphere is involved (Elliott, 1985). Because the left-hemisphere is specialized for sequential movement production, more interhemispheric crosstalk via the corpus callosum would result for someone producing the desired movement with their non-dominant hand if trained with their dominant hand. However, stored motor information would already be present in the left-hemisphere for the right-hand to access directly if a skill had been learned previously with the left hand. My findings are consistent with this explanation of asymmetric interlimb transfer of training effects.

General Discussion

The present study found that self-regulated practice schedules were beneficial for motor learning. Moreover, it was revealed that a variety of strategies were adopted by individuals in the self-regulated groups when organizing practice (e.g., some chose to switch frequently while others chose to switch less frequently) in tasks of varying complexity. So essentially this study revealed *how* participants organized their practice schedules as task complexity changed, however, investigating *why* individuals chose to switch when they did is also of theoretical interest. By examining such a question, a deeper understanding of the strategies individuals use when organizing practice in a self-regulated fashion could be attained.

Why Did People Switch?

Performance Contingent? Current self-regulation research has begun to offer explanations of why self-regulation may be effective and postulates as to what the mechanisms are that underlie this effect. One such factor that has been investigated is whether individuals base self-regulating decisions on their performance. Recently, Chiviacowsky and Wulf (2002) investigated the effects of self-regulated feedback on a sequential timing task compared to a yoked control group. These researchers administered a questionnaire after the practice phase to try to determine when participants chose to receive feedback. Interestingly, 67% of the self-regulated group reported that they asked for feedback after a good trial. When asked "when did you not ask for feedback", 73% of the self-regulated group reported "after bad trials". The yoked participants, who had no choice in their schedules of feedback, often reported that they did not receive feedback after their preferred trials, with most suggesting as well that they would have preferred feedback after good trials. To measure whether individuals' self-reports of receiving feedback after good trials was accurate; these researchers compared performance on feedback trials versus no-feedback trials between the groups. For the self-regulated group, Chiviacowsky and Wulf found that error rates were lower on trials followed by (requested) feedback than trials for which feedback was not requested, whereas there was the opposite trend for the yoked group. In addition, error scores were lower for the self-regulated groups compared to the yoked group on feedback trials, with no differences between the groups on no-feedback trials.

These findings contrast directly with some of the theoretical interpretations of the role of feedback for learning. Specifically, the guidance hypothesis (for a review, see Salmoni, Schmidt, & Walter, 1984) would suggest that feedback after bad trials would be particularly important and useful because this feedback could guide the participant toward the correct movement. Bandwidth designs are constructed based on the principle that qualitative, confirmatory feedback is given following good trials, but that quantitative, explicit information is provided when errors exceed a certain tolerance of acceptability. The results of Chiviacowsky and Wulf (2002), however, suggest that when the learners think feedback is important for effective learning may not be congruent with the theoretical concepts of the role of augmented feedback.

Manipulating self-regulated practice schedules with a key pressing task, Wu and Magill (2005) adapted the questionnaire used by Chiviacowsky and Wulf (2002) by essentially replacing "feedback" with "switch". Interestingly, the questionnaire results were similar – individuals reported switching between tasks predominantly after good trials versus bad trials, and that self-regulation allowed them to use all the strategies they were interested in using during acquisition (although it was not documented what these strategies were). Moreover, individuals in the yoked group often reported that the practice schedule they were given did not match when they would have chosen to switch. A drawback to this study is that these authors did not perform specific analyses on the data to determine whether what was reported actually matched performance. Specifically, it could not be said for certain whether participants' subjective estimation of their own performance was truly representative of their actual performance without an objective analysis.

To test whether individuals were using a performance-contingent strategy for making their decision to switch in the present study (i.e., perhaps they were switching after *good trials*). A separate ANOVA was conducted similar to the one conducted by Chiviacowsky and Wulf (2002). Specifically, a 2 Task Complexity (Easy, Hard) by 2 Group (Self-Regulated, Yoked) by 2 Trial (Trial Prior to Switch, Trial of Switch) mixed ANOVA was conducted on MT and accuracy measures with trial as a repeated measure. In this analysis, performance data of the Trial factor always came from the *same* pattern. The hypothesis would be that if individuals were basing their decision to switch in a performance-contingent manner, then one would expect to see better performance (e.g., faster movement times, increased accuracy) on the switch trial compared to the trial prior to the switch trial of the same pattern for the self-regulated group; whereas one would not expect this same pattern with the yoked participants even though these individuals had the exact same practice schedule[6]. Results of this analysis for MT revealed a main effect for Task Complexity, $F(1,16)=86.21$, $p<.01$, as well as a significant interaction of Group and Trial, $F(1,16)=4.62$, $p<.05$. The interaction revealed that MTs on switch trials were significantly faster than the trials prior to the switch for the self-regulated groups, while there was no difference in trial performance for the yoked groups (see Figure 14). No other effects or interactions were significant for MT. Analysis of pattern errors revealed no significant effects or interactions, however, there was a trend for fewer pattern errors to occur on switch trials compared to non-switch trials for the self-regulated group ($p=0.11$) (see Figure 15). A similar trend ($p=0.47$) also emerged in that fewer cursor errors occurred on switch trials compared to non-switch trials for the self-regulated group (see Figure 16). These results are in general, similar to the findings of Chiviacowsky and Wulf (2002) and suggest that individuals may base their decision to switch on performance-contingent factors, and this may be an effective strategy for motor learning.

---

6 Not all participants of the self-regulated, and therefore yoked groups, were included in the present analysis. Specifically, only 5 of the 12 from each group were included. The reason for this was the following: first, there was variability within the self-regulated groups in regard to the amount of switches that occurred. For instance, some individuals chose a completely blocked ordering, while some practiced in large, structured chunks (8 or 16 trials of one pattern before switching). Subsequently, means for the prior to or switch trials would be gathered from only a few cells of data and most likely not represent a true mean performance score. For these individuals it is highly likely that they were not using a performance-contingent strategy, but rather a more global strategy based on the information that was given to them. Recall that individuals were shown after every trial a screen that presented how many trials were remaining for each pattern. For example, if a participant performed pattern A on trial 1; after completing this pattern and receiving feedback, they would be shown a screen that said "Pattern A: 31 trials remaining, Pattern B: 32 trials remaining, Pattern C: 32 trials remaining, Pattern D: 32 trials remaining". What some individuals were likely doing was taking this information and deciding on a more global strategy like "okay well, 32 in each pattern, so I guess I could practice in multiples of that number". So instead of basing their switch decision on actual performance they may have been focussing more on making patterns with the trials, and not focussing as much on cognitively processing the self-schedule practice order, or making performance-contingent switch decisions. Therefore, only the participants of the 'Switch Often' subgroup from the Switch Frequency analysis mentioned previously were used in the present analysis. These individuals were thought to be good candidates because they had multiple switches and it appeared that there was no obvious pattern to their switch decisions (i.e., no obvious chunking or blocking of trials).

Specifically, this study revealed that individuals perhaps set criteria for themselves to decrease MT (at least from the previous trial) as well as to be relatively error-free before allowing themselves to switch.

Based on the results of the above analysis, it is evident that individuals may have been using performance-contingent goals or strategies for their switch decisions. However, we know that performance-contingent switching is not solely responsible for the benefits of self-regulation in this study. Remember, no differences between Switch Frequency subgroups were found in acquisition or retention when comparing those individuals who chose to switch rarely with those who chose to switch often. If it was those individuals who switched more often, and perhaps made performance-contingent switch decisions that were the ones predominantly responsible for the beneficial effects of self-regulation, one would have expected to see this reflected in the results. If this is the case one would predict that these individuals would do better in acquisition and retention compared to the self-regulated participants who switched less frequently. Instead, there were no differences between subgroups. So although self-regulation may allow for use of performance-contingent strategies, there seems to be a more general benefit of self-regulation for effective motor learning and there are more mechanisms involved in why self-regulation is effective.

Findings from this study and previous studies (Chiviacowsky et al., 2002, 2005) support the notion that self-regulation may be effective because it provides learners the opportunity to organize their learning environment in a fashion that is contingent upon their own performance. In this regard, individuals may be able to set incremental criteria or goals for them to be successful with before continuing on to a new element of the task. This idea has important implications for real-life setting and could reflect more realistic daily living methods of learning for individuals. Nevertheless, this is not the whole story to self-regulation. In general it was found in this study that self-regulation was effective for motor retention. However, when analyses were conducted on the self-regulated groups that were split into those who switched frequently and those who choose to switch less frequently, there were no significant differences in retention performance. This finding suggests that it may be self-regulation in general and not the control of a specific aspect of the learning context that may be beneficial. Indeed, Bund and Wiemeyer (2004) found that self-regulation in general produced effective results for table-tennis serving, regardless of whether individuals could control the feedback they received (e.g., videotape of a model) or other practice dimensions (e.g., speed and direction of on-coming balls).

So Why is Self-Regulation Effective for Motor Learning? Other Mechanisms

Despite the fact that self-regulation benefits on motor learning appear to be a rather robust and perhaps general phenomenon, it is still relatively unclear why self-regulation is effective. Indeed most explanations have been adapted from literature on cognitive learning and are vague in terms of specific motor control and/or learning mechanisms. Although the present study was not conducted to specifically address this issue, it is worth mentioning other mechanisms to gain a better understanding for why self-regulation may be effective for motor learning.

Self-regulation is a complex process. Zimmerman (1986, 1994) has proposed that the degree to which individuals are metacognitively, motivationally, and behaviourally active participants in their own learning process contributes to the effectiveness of self-regulation. Zimmerman stated: "Metacognitively, self-regulated learners are persons who plan, organize, self-instruct, self-monitor, and self-evaluate at various stages during the learning process. Motivationally, self-regulated learners perceive themselves as competent, self-efficacious, and autonomous. Behaviourally, self-regulated learners select, structure, and create environments that optimize learning" (p.308). The present study captures elements of Zimmerman's third behavioural subprocess of effective motor learning, as the self-regulated groups who indeed structured their own practice, showed enhanced motor learning. Although not demonstrated in this study, cognitive and motivational factors have been shown to play a role in motor learning (e.g., Bund & Wiemeyer, 2004; Chen & Singer, 1992; Simon & Bjork, 2001, 2002; Zimmerman & Kitsantas, 1996).

Cognitive strategies have been defined as "sequences of higher-order mental procedures that enable learners to influence information processing positively and manipulate learning and performance situations properly in order to optimize achievement outcomes" and metacognitive experiences as "conscious experiences about cognitive goals, cognitive actions, and/or metacognitive knowledge" (Chen & Singer, 1992, p.279, 283). It has been suggested that perception of self-control enhances learning because it leads to more active involvement of the learner in the learning process which in turn promotes a deeper processing of relevant information (McCombs, 1989; Watkins, 1984). For example, Entwistle, Entwisle, and Tait (1993) found that self-regulated learning correlated significantly with more effective and elaborative study strategies in contrast to simple, less effective rehearsal strategies. From a cognitive viewpoint then, self-regulation is effective because it allows for greater self-awareness and deeper information processing in the learning experience.

Not only have cognitive mechanisms been put forth, but motivational reasons have also been suggested to contribute to the beneficial effects of self-regulation. For instance, increased levels of motivation have been shown to lead to an enhanced sense of self-efficacy which can encourage the learner to set goals for themselves (e.g., Bandura, 1993; Boekaerts, 1996; Meece, 1994). In an interesting study, Zimmerman and Kitsantas (1996) had individuals learn how to throw a dart at a standard dartboard. These authors split participants into groups that differed based on the type of goals they used during practice. Specifically, some were told to focus on *process* goals, "methods and strategies that can help students to master a particular task" (e.g., focusing on improving technique) and the others to focus on *product* goals, "which specify the outcomes of learning efforts" (e.g., focus on getting a high score). Results revealed that those who focussed on process goals learned to throw the dart more effectively. Moreover, these individuals expressed greater self-efficacy, greater satisfaction with their dart throwing performance, and preferred the dart throwing task more than those given product goals. Although these authors controlled which type of goal individuals were regulating, it seems reasonable to think that using process goals may be more realistic or representative of what individuals would use when learning a task or skill in real life, because it may increase enjoyment of the task, self-efficacy and motivation. Bund and Wiemeyer (2004) demonstrated that not only did those individuals that were given self-control during practice perform better in retention than yoked controls but these individuals also reported significantly stronger self-efficacy beliefs compared to yoked controls throughout the learning process.

Taken together, self-regulation may be effective for motor learning because individuals can organize practice in a way that is optimal for them, but also in a way that cognitively engages and motivates them. Although developed to describe effective self-regulated academic learning, social-cognitive theorists (Bandura, 1986; Zimmerman, 1989) have proposed a model in which personal, behavioural, and environmental sources of control are reciprocally and constantly changing during the course of learning and performance. The degree to which each source is self-monitored and adjusted using a self-oriented feedback loop determines the effectiveness of self-regulation. Indeed, such a social-cognitive model of self-regulation could certainly be applied to self-regulatory processes in motor learning and represents a rich opportunity for future research.

Conclusion

The present study aimed to examine how self-regulation impacts the motor learning process as a function of task complexity. It was found that self-regulation was beneficial for motor retention. Moreover, although strategies varied for self-regulated learners depending on the level of complexity of task performed, this did not affect the overall benefit to motor learning. This study adds to the growing body of evidence that self-regulated practice scheduling is effective for motor learning, and advances the literature by showing benefit of self-regulation for tasks of varying complexity. Self-regulation in motor learning research appears to have merit and offers fruitful avenues for further theoretical as well as application research in the future.

References

Albaret, J.M., & Thon, B. (1998). Differential effects of task complexity on contextual interference in a drawing task. *Acta Psychologica, 100,* 9-24.

Baddeley, A.D., & Longman, D.J.A. (1978). The influence of length and frequency of training session on the rate of learning to type. *Ergonomics, 21,* 627-635.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28,* 117-148.

Battig, W.F. (1979). The flexibility of human memory. In L.S. Cermak & F.I.M. Craik (Eds.), *Levels of processing in human memory* (pp. 23-44). Hillsdale, NJ: Erlbaum.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European Psychologist, 1,* 100-112.

Brady, F. (2004). Contextual interference: A meta-analytic study. *Perceptual and Motor Skills, 99,* 116-126.

Bund, A., & Wiemeyer, J. (2004). *Self-controlled learning of a complex motor skill: Effects of the learners' preferences on performance and self-efficacy.* Manuscript submitted for publication.

Chen, D., & Singer, R.N. (1992). Self-regulation and cognitive strategies in sport participation. *International Journal of Sport Psychology, 23,* 277-300.

Chiviacowsky, S., & Wulf, G. (2002). Self-controlled feedback: Does it enhance learning because performers get feedback when they need it? *Research Quarterly for Exercise and Sport, 73,* 408-415.

Chiviacowsky, S., & Wulf, G. (2005). Self-controlled feedback is effective if it is based on the learner's performance. *Research Quarterly for Exercise and Sport, 76,* 42-8.

Dail, T.K., & Christina, R.W. (2004). Distribution of practice and metacognition in learning and long-term retention of a discrete motor task. *Research Quarterly for Exercise and Sport, 75,* 148-155.

Dunlosky, J., & Nelson, T.O. (1992). Importance of the kind of cue for judgments of learning (JOL) and the delayed-JOL effect. *Memory & Cognition, 20,* 374-380.

Edwards, J.M., & Elliott, D. (1987). Effect of unimanual training on contralateral motor overflow in children and adults. *Developmental Neuropsychology, 3,* 299-309.

Elliott, D. (1985). Manual asymmetries in the performance of sequential movement by adolescents and adults with Down syndrome. *American Journal of Mental Deficiency, 90,* 90-97.

Entwistle, N.J., Entwistle, A., & Tait, H. (1993). Academic understanding and contexts to enhance it: a perspective from research on student learning. In T. Duffy, J. Lowyck, & D.H. Jonassen (Eds.), *Designing environments for constructive learning* (pp. 331-357). Berlin: Springer.

Guadagnoli, M.A., & Lee, T.D. (2004). Challenge point: A framework for conceptualizing the effects of various practice conditions in motor learning. *Journal of Motor Behavior, 36,* 212-224.

Janelle, C.M., Barba, D.A., Frehlich, S.G., Tennant, L.K., & Cauraugh, J.H. (1997). Maximizing performance feedback effectiveness through videotape replay and a self-controlled learning environment. *Research Quarterly for Exercise and Sport, 68,* 269-279.

Janelle, C.M., Kim, J., & Singer, R.N. (1995). Subject-controlled performance feedback and learning of a closed motor skill. *Perceptual and Motor Skills, 81,* 627-634.

Kimball, D.R., & Metcalfe, J. (2003). Delaying judgments of learning affects memory, not metamemory. *Memory & Cognition, 31,* 918-929.

Lee, T.D., & Genovese, E.D. (1988). Distribution of practice in motor skill acquisition: Learning and performance effects reconsidered. *Research Quarterly for Exercise and Sport, 59,* 277-287.

Lee, T.D., & Magill, R.A. (1983). The locus of contextual interference in motor-skill acquisition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9,* 730-746.

Lee, T.D., & Magill, R.A. (1985). Can forgetting facilitate skill acquisition? In D. Goodman, R.B. Wilberg, & I.M Franks (Eds.), *Differing perspectives in motor learning, memory, and control* (pp. 3-22). Amsterdam: Elsevier.

Lee, T.D., Wishart, L.R., Cunningham, S., & Carnahan, H. (1997). Modeled timing information during random practice eliminates the contextual interference effect. *Research Quarterly for Exercise and Sport, 68,* 100-105.

Magill, R.A. (2001). Augmented feedback in motor skill acquisition. In Singer, R.N., Hausenblas, H.A., & Janelle, C.M. (Eds.). *Handbook of sport psychology* (p 86-114). New York: Wiley.

Magill, R.A., & Hall, K.G. (1990). A review of the contextual interference effect in motor skill acquisition. *Human Movement Science, 9,* 241-289.

McCombs, B. (1989). Self-regulated learning and academic achievement: a phenomenological view. In B.J. Zimmerman & D.H. Schunk (Eds.), *Self-regulated learning and academic achievement. Theory, research, and practice* (pp. 51-82). New York: Springer.

Meece, J.L. (1994). The role of motivation in self-regulated learning. In D.H. Schunk & B.J. Zimmerman (Eds.), *Self-regulation of learning and performance: Issues and educational applications* (pp. 25-44). Hillsdale, NJ: Erlbaum.

Metcalfe, J., & Shimamura, A.P. (Eds.). (1994). *Metacognition: Knowing about knowing*. Cambridge, MA: MIT Press.

Richards, R.M., & Nelson, T.O. (2004). Effect of the difficulty of prior items on the magnitude of judgments of learning for subsequent items. *American Journal of Psychology, 117,* 81-91.

Salmoni, A.W., Schmidt, R.A., & Walter, C.B. (1984). Knowledge of results and motor learning: a review and critical reappraisal. *Psychological Bulletin, 95,* 355 – 386.

Shea, J.B., & Morgan, R.L. (1979). Contextual interference effects on the acquisition, retention, and transfer of a motor skill. *Journal of Experimental Psychology: Human Learning and Memory, 5,* 179-187.

Shea, J.B., & Zimny, S.T. (1983). Context effects in memory and learning movement information. In R.A. Magill (Ed.), *Memory and control of action* (pp. 345-366). Amsterdam: Elsevier.

Shea, J.B., & Zimny, S.T. (1988). Knowledge incorporation in motor representation. In O.G. Meijer & K. Roth (Eds.), *Complex movement behaviour: 'The' motor-action controversy* (pp. 289-314). Amsterdam: Elsevier.

Simon, D.A., & Bjork, R.A. (2001). Metacognition in motor learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27,* 907-912.

Simon, D.A., & Bjork, R.A. (2002). Models of performance in learning multisegment movement tasks: Consequences for acquisition, retention, and judgments of learning. *Journal of Experimental Psychology: Applied, 8,* 222-232.

Son, L.K. (2004). Spacing one's study: evidence for a metacognitive control strategy. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30,* 601-604.

Taylor, H.G., & Heilman, K.M. (1980). Left-hemisphere motor dominance in right handers. *Cortex, 16,* 587-603.

Titzer, R., Shea, J.B., & Romack, J. (1993). The effect of learner control on the acquisition and retention of a motor task. Paper presented at the annual conference of the

North American Society for the Psychology of Sport and Physical Activity, Brainerd, MN (abstract published in *Journal of Sport and Exercise Psychology, 13,* S84).

Watkins, D. (1984). Students' perceptions of factors influencing tertiary learning. *Higher Education Research Developments, 3,* 33-50.

Wright, D.L. (1991). The role of intertask and intratask processing in acquisition and retention of motor skills. *Journal of Motor Behavior, 23,* 139-145.

Wright, D.L., Li, Y., & Whitacre, C. (1992). The contribution of elaborative processing to the contextual interference effect. *Research Quarterly for Exercise and Sport, 63,* 30-37.

Wrisberg, C.A., & Pein, R.L. (2002). Note on learners' control of the frequency of model presentation during skill acquisition. *Perceptual and Motor Skills, 94,* 792-794.

Wu, W., & Magill, R.A. (2004). To dictate or not: The exploration of a self-regulated practice schedule. Paper presented at the annual conference of the North American Society for the Psychology of Sport and Physical Activity, Vancouver, BC (abstract published in *Journal of Sport and Exercise Psychology, 26,* S202).

Wu, W., & Magill, R.A. (2005). Allowing learners to choose: Self-regulated practice schedules for learning multiple movement patterns. Paper presented at the annual conference of the North American Society for the Psychology of Sport and Physical Activity, St. Pete's, FL (abstract published in *Journal of Sport and Exercise Psychology, 27,* S161).

Wulf, G., Raupach, M., & Pfeiffer, F. (2005). Self-controlled observational practice enhances learning. *Research Quarterly for Exercise and Sport, 76,* 107-111.

Wulf G, Toole T. (1999). Physical assistance devices in complex motor skill learning: benefits of a self-controlled practice schedule. *Research Quarterly for Exercise and Sport, 70,* 265–272.

Wulf, G., & Shea, C.H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin & Review, 9,* 185-211.

Zimmerman, B.J. (1986). Development of self-regulated learning: Which are the key subprocesses? *Contemporary Educational Psychology, 16,* 307-313.

Zimmerman, B.J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81,* 329-339.

Zimmerman, B.J. (1994). Dimensions of academic self-regulation: A conceptual framework for education. In D.H. Schunk & B.J. Zimmerman (Eds.), *Self-regulation of learning and performance: Issues and educational applications* (pp. 3-21). Hillsdale, NJ: Erlbaum.

Zimmerman, B.J., & Kitsantas, A. (1996). Self-regulated learning of a motoric skill: The role of goal setting and self-monitoring. *Journal of Applied Sport Psychology, 8,* 60-75.

Table 1.
Number of switches made by self-regulated groups in acquisition as a function of task complexity, switch frequency, and block.

Task Complexity	Switch Frequency	Acquisition Block 1	2	3	4	5	6	7	8	Total
Easy										
	Rarely	0	0	1	0	1	0	1	0	3
		1	0	1	0	1	0	1	0	4
		1	3	1	0	1	0	1	0	7
		0	1	1	0	1	1	2	7	13
		2	2	2	2	2	2	2	1	15
		5	1	2	2	3	0	2	1	16
		9	5	0	1	1	0	1	0	17
	Often	14	1	1	1	0	1	6	16	40
		4	6	2	2	4	6	10	14	48
		15	15	12	8	11	10	13	13	97
		14	13	14	14	10	13	15	14	107
		14	15	14	15	14	14	16	15	117
Hard										
	Rarely	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	2	0	1	0	3
		0	3	0	1	0	1	0	12	17
		7	4	2	2	1	0	1	0	17
		4	2	1	1	0	1	4	9	22
	Often	7	4	4	4	4	4	4	6	37
		3	12	2	2	11	8	5	3	46
		3	5	6	9	16	12	9	6	66
		14	10	9	10	10	9	5	5	72
		12	11	15	6	8	12	13	11	88

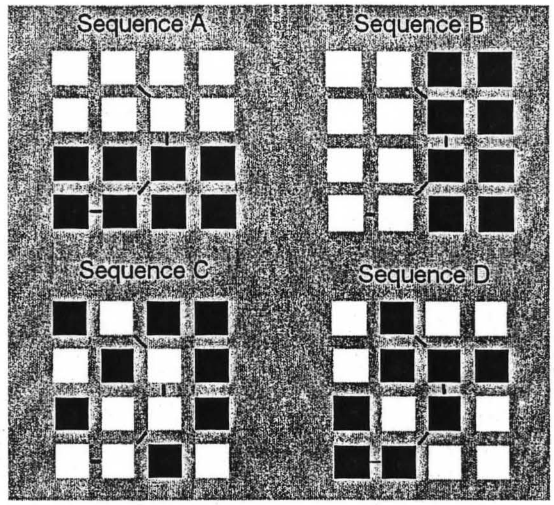
Table 2a.
Mean movement time (MT), planning time (PT), pattern errors, and cursor errors in acquisition, retention, and transfer as a function of group and block for tasks of easy complexity.

		Acquisition								Retention	Transfer	
		Block									Hand	
		1	2	3	4	5	6	7	8	R	Dom	NonDom
MT (ms)	Blocked	1335	1107	1066	1040	1006	983	976	968	1125	1713	3113
	Random	1383	1098	974	944	859	876	841	851	949	1694	2702
	Self-Regulated	1327	1197	1136	1101	1068	1041	1019	1012	906	1643	2512
	Yoked	1260	935	867	827	787	780	764	732	869	1541	2655
PT (ms)	Blocked	973	436	407	405	361	360	347	398	827	903	1159
	Random	1924	1141	910	812	805	760	780	901	963	1585	1813
	Self-Regulated	1463	866	765	683	680	762	595	723	1046	1112	1472
	Yoked	1312	773	685	640	587	572	601	632	871	1155	1477
Pattern Errors (out of 20)	Blocked	0.3	0.1	0.1	0.0	0.2	0.1	0.1	0.3	0.4	1	3
	Random	1.0	0.1	0.2	0.0	0.0	0.1	0.1	0.2	0.2	2	2
	Self-Regulated	0.9	0.4	0.4	0.3	0.1	0.1	0.1	0.1	0.5	1	1
	Yoked	0.4	0.5	0.1	0.3	0.1	0.2	0.2	0.2	0.9	1	1
Cursor Errors (out of 20)	Blocked	0.8	0.8	0.8	0.9	0.8	1.0	1.0	0.8	1.0	1.1	2
	Random	0.5	0.5	0.6	0.9	1.0	1.5	1.3	1.2	1.4	1.8	1.6
	Self-Regulated	1.2	1.1	1.0	1.3	1.0	1.2	1.5	1.7	1.2	1.4	2.3
	Yoked	1.1	0.8	1.2	0.8	1.1	1.1	1.1	1.5	1.6	1.5	2.4

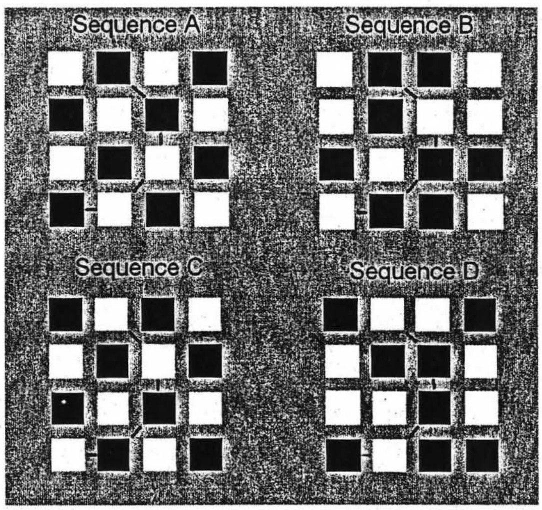
Table 2b.
Mean movement time (MT), planning time (PT), pattern errors, and cursor errors in acquisition, retention, and transfer as a function of group and block for tasks of hard complexity.

		Acquisition								Retention	Transfer	
		Block									Hand	
		1	2	3	4	5	6	7	8	R	Dom	NonDom
MT (ms)	Blocked	1992	1675	1589	1544	1474	1448	1402	1400	1605	1660	1952
	Random	2518	2044	1888	1854	1793	1694	1710	1611	1796	1979	2071
	Self-Regulated	2261	1982	1912	1845	1863	1814	1812	1797	1686	1927	2016
	Yoked	2383	2047	1967	1847	1820	1755	1754	1744	1855	1902	2221
PT (ms)	Blocked	1722	668	705	661	583	810	499	620	1516	1867	1704
	Random	1070	984	915	932	671	719	760	850	1042	1229	1403
	Self-Regulated	1732	1134	948	902	1004	993	898	919	1257	1347	1462
	Yoked	2143	1373	1173	821	830	738	802	972	1445	1184	1158
Pattern Errors (out of 20)	Blocked	0.9	0.4	0.3	0.4	0.4	0.1	0.4	0.4	1.0	0.8	2.8
	Random	0.3	0.3	0.4	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.9
	Self-Regulated	0.6	0.2	0.2	0.3	0.4	0.6	0.6	0.4	0.3	0.6	0.3
	Yoked	0.4	0.1	0.5	0.2	0.4	0.5	0.3	0.2	0.2	0.3	0.7
Cursor Errors (out of 20)	Blocked	1.8	1.8	2.2	2.2	1.5	2.1	2.2	2.1	2.4	1	2.8
	Random	0.6	1.2	0.8	1.2	0.9	1.2	1.1	1.6	1.4	0.9	1.4
	Self-Regulated	1.4	1.5	0.8	0.8	1.5	2.0	1.8	2.4	1.2	0.7	1.1
	Yoked	0.9	1.3	1.2	0.9	0.9	1.0	1.2	1.2	0.9	0.7	1.7

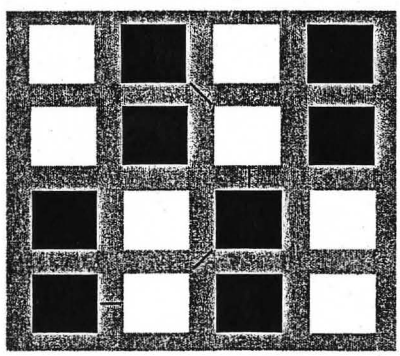
Easy Patterns

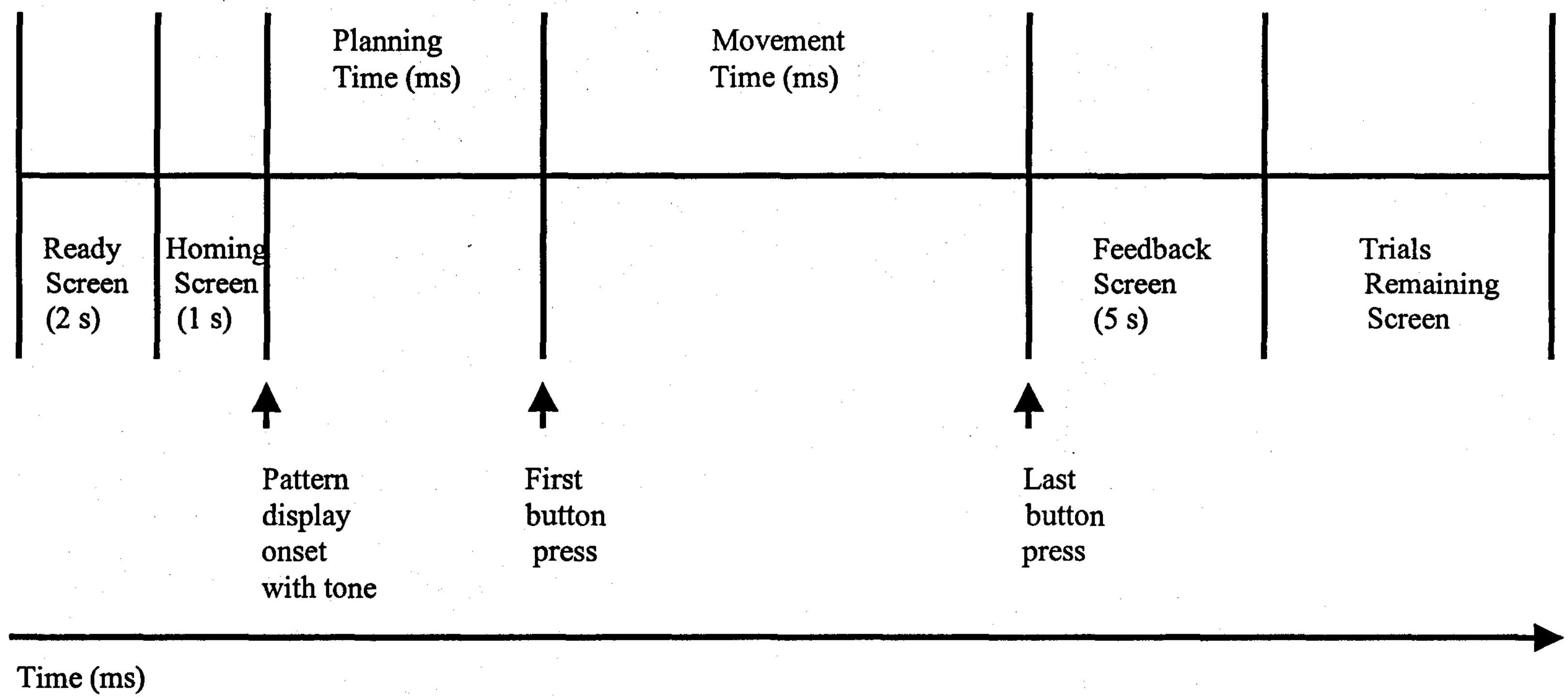


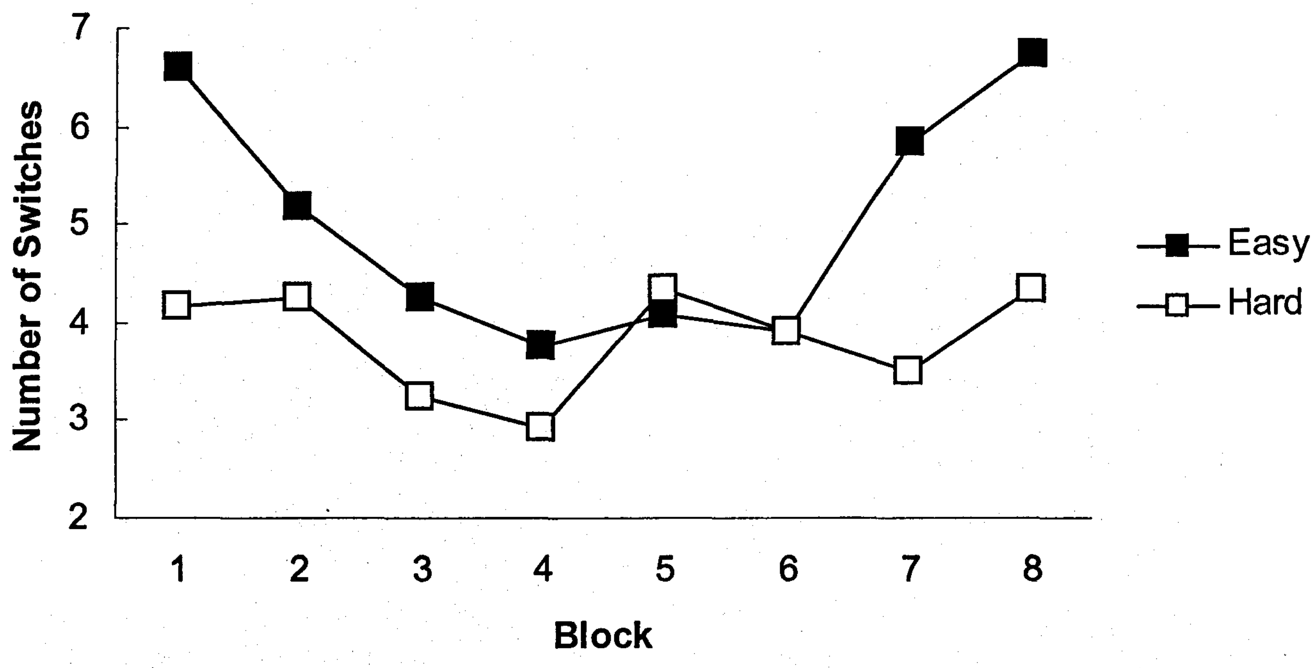
Hard Patterns

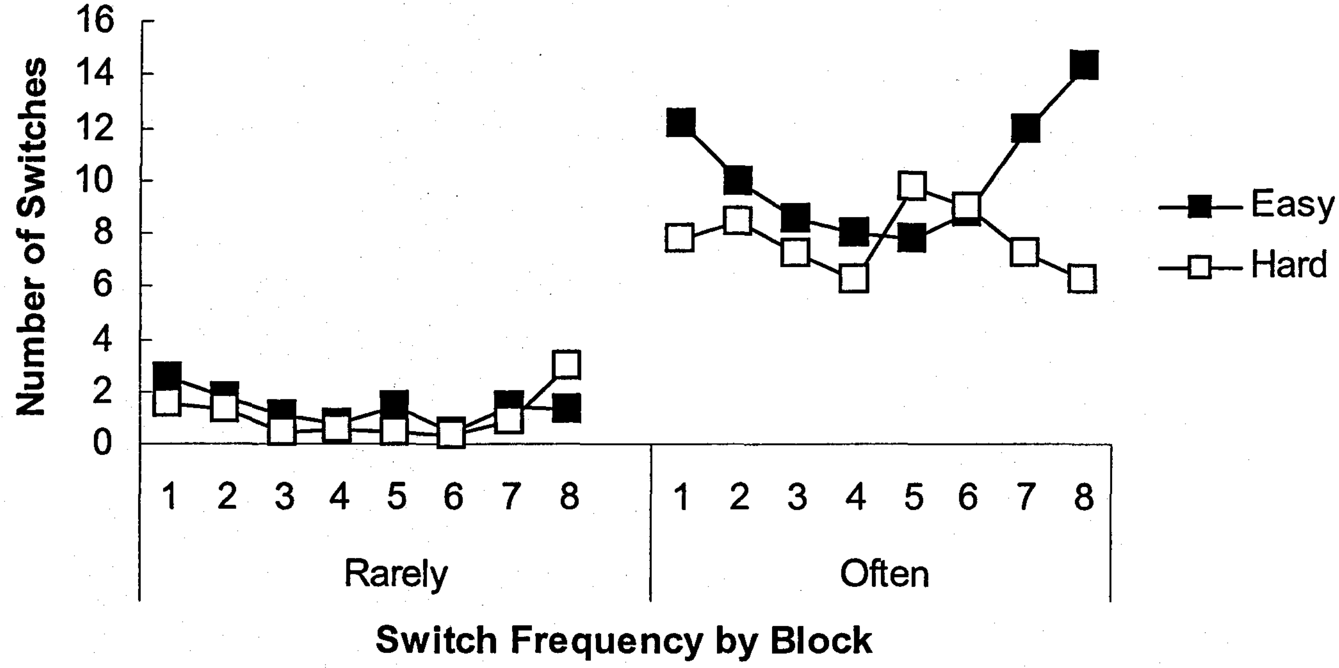


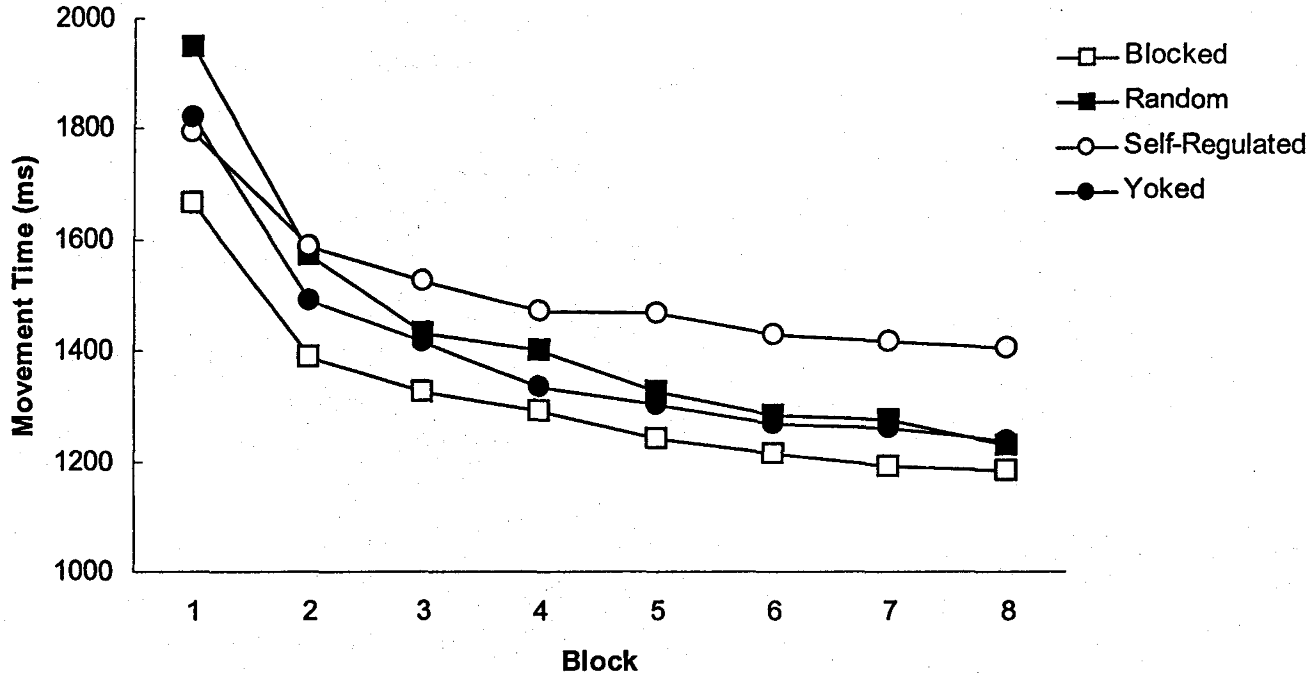
Transfer Pattern

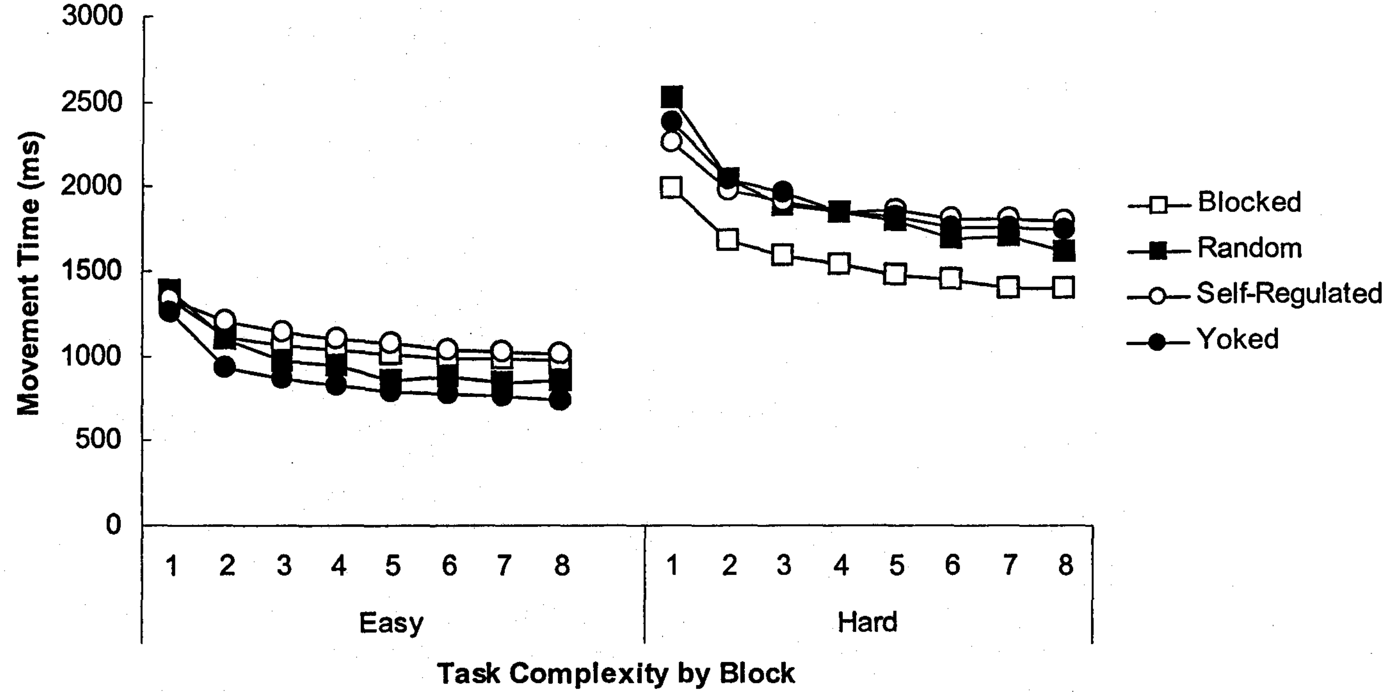


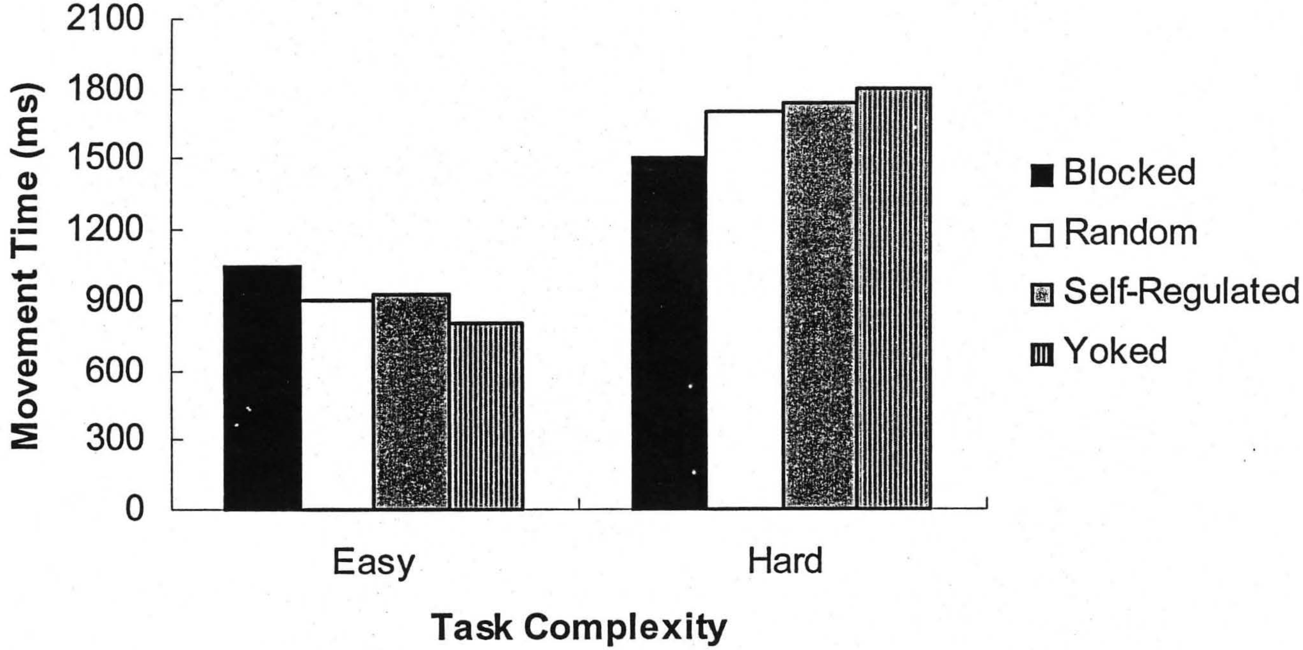

Planning
Time (ms)
Movement
Time (ms)
Ready
Screen
(2 s)
Homing
Screen
(1 s)
Feedback
Screen
(5 s)
Trials
Remaining
Screen
Pattern
display
onset
with tone
First
button
press
Last
button
press
Time (ms)

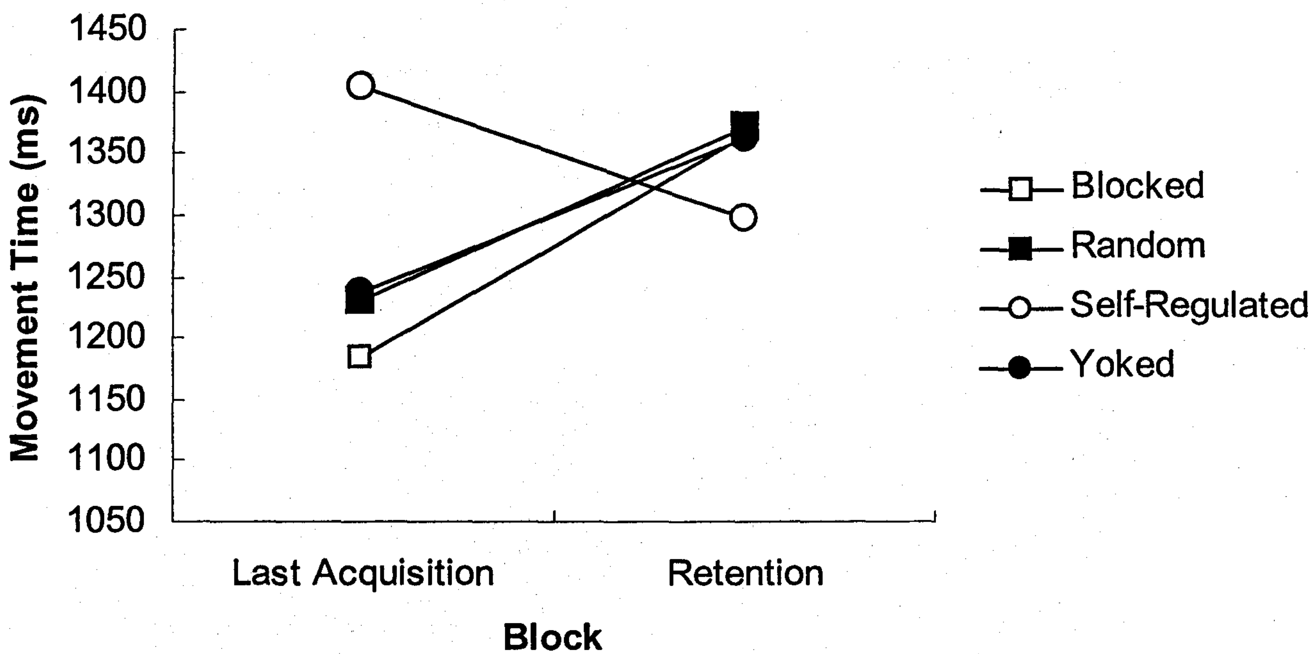

Number of Switches
7
6
5
4
3
2
1
2
3
4
5
6
7
8
Block
Easy
Hard

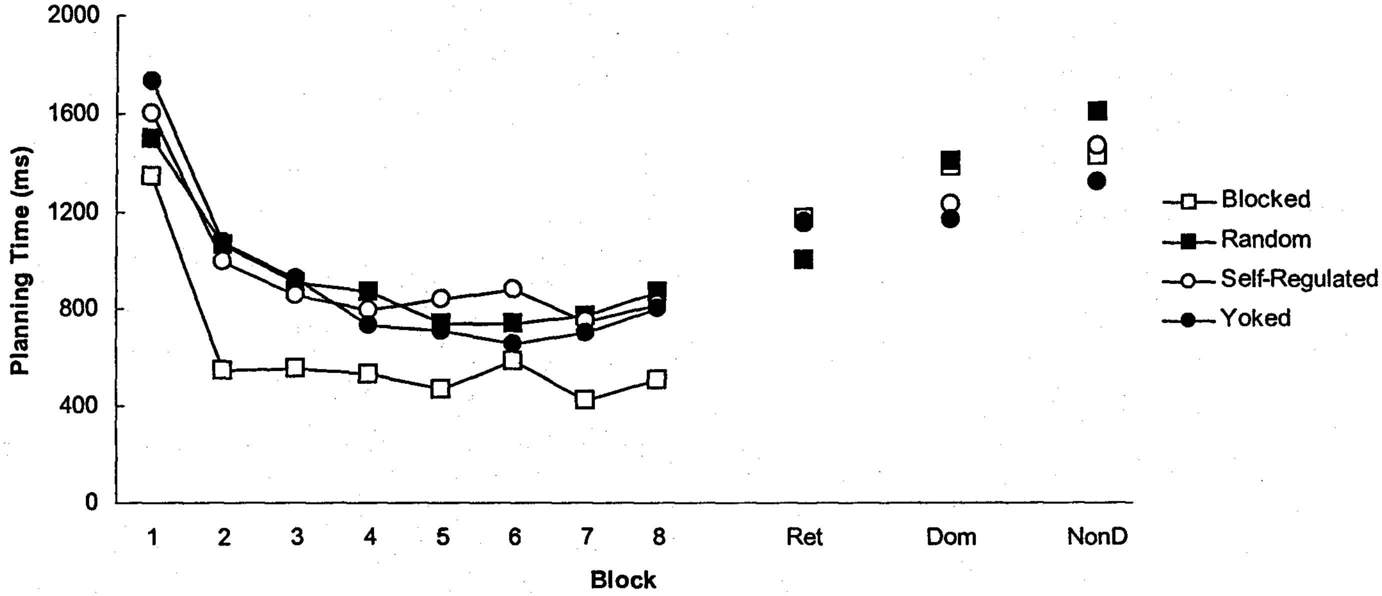

16
14
12
10
8
6
4
2
0
Number of Switches
1 2 3 4 5 6 7 8
Rarely
1 2 3 4 5 6 7 8
Often
Switch Frequency by Block
Easy
Hard


2000
1800
1600
1400
1200
1000
Movement Time (ms)
1
2
3
4
5
6
7
8
Block
Blocked
Random
Self-Regulated
Yoked

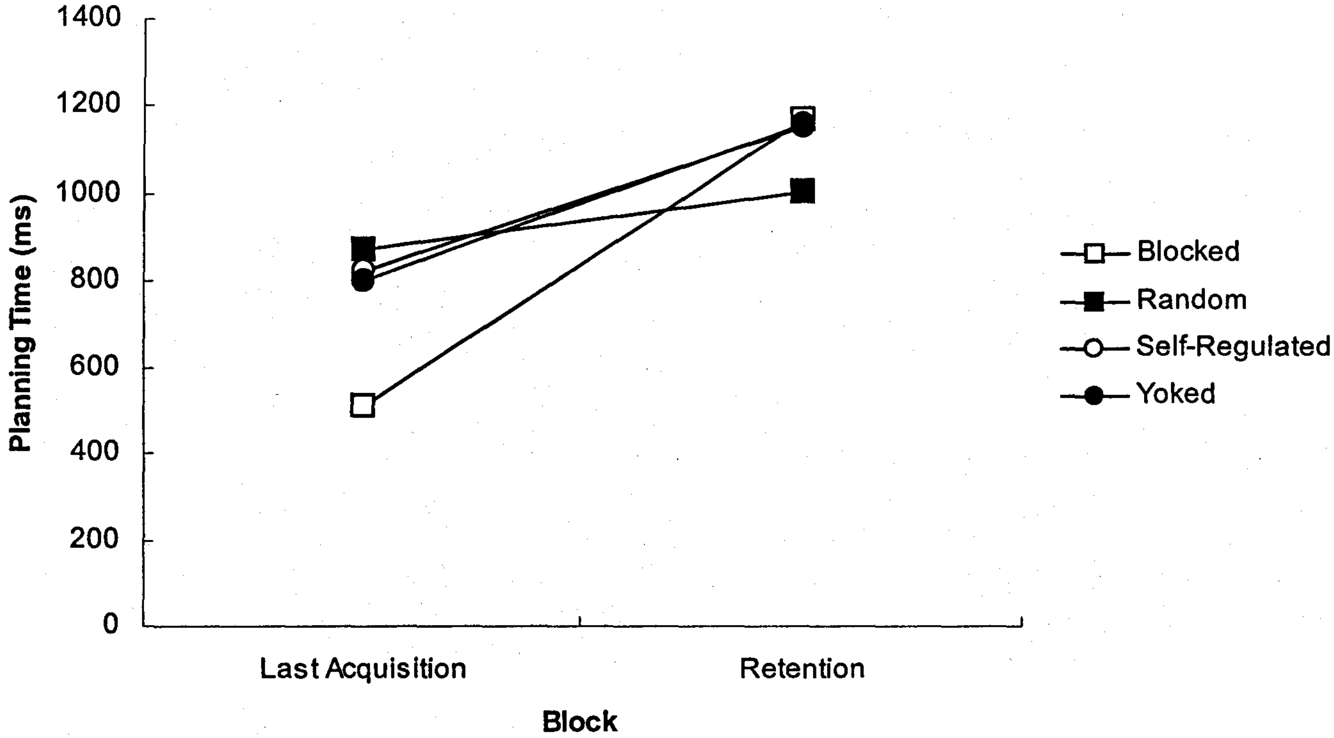

3000
2500
2000
1500
1000
500
0
Movement Time (ms)
1
2
3
4
5
6
7
8
Easy
Hard
Task Complexity by Block
Blocked
Random
Self-Regulated
Yoked

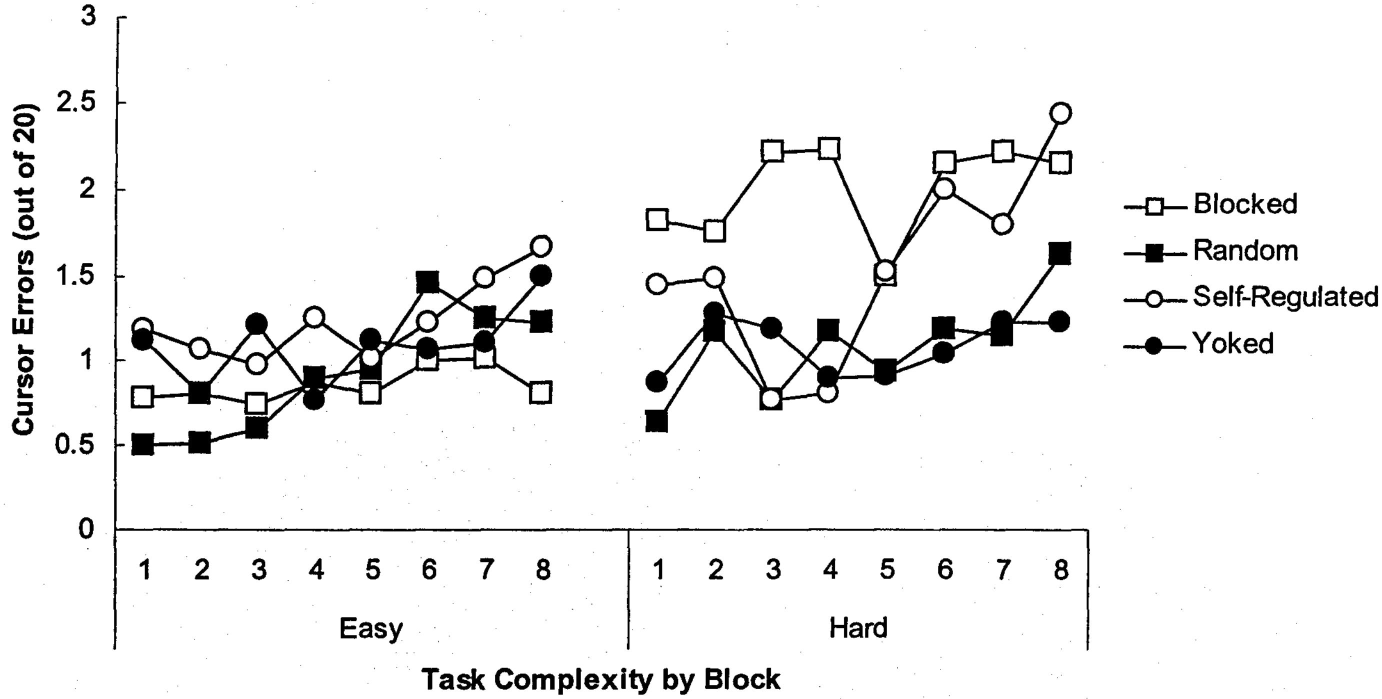

2100
1800
1500
1200
900
600
300
0
Movement Time (ms)
Easy
Hard
Task Complexity
Blocked
Random
Self-Regulated
Yoked

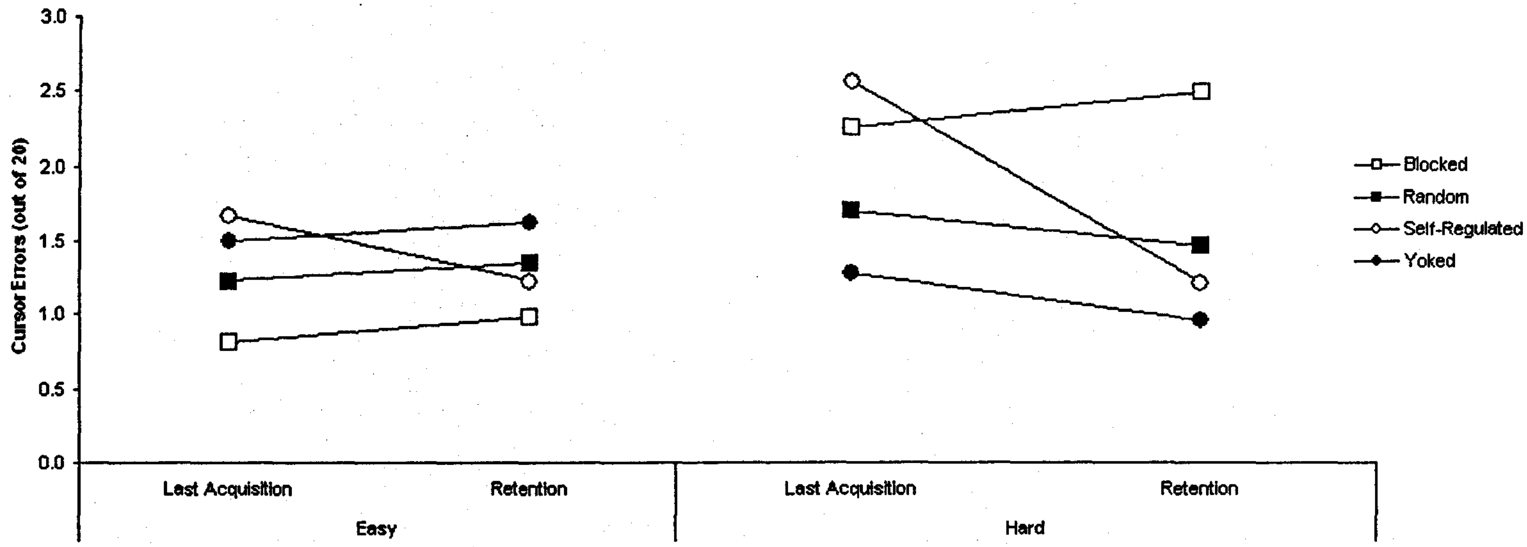

1450
1400
1350
1300
1250
1200
1150
1100
1050
Movement Time (ms)
Last Acquisition
Retention
Block
Blocked
Random
Self-Regulated
Yoked



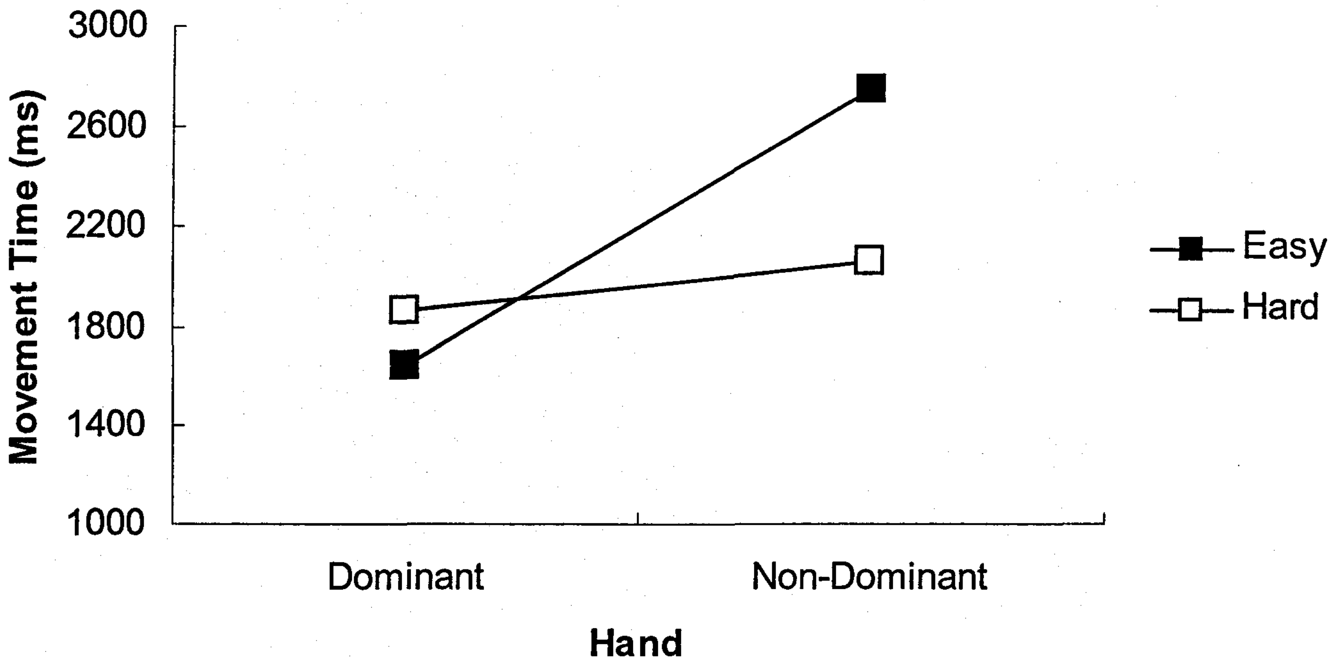
2000
1600
1200
800
400
0
Planning Time (ms)
1
2
3
4
5
6
7
8
Ret
Dom
NonD
Block
Blocked
Random
Self-Regulated
Yoked

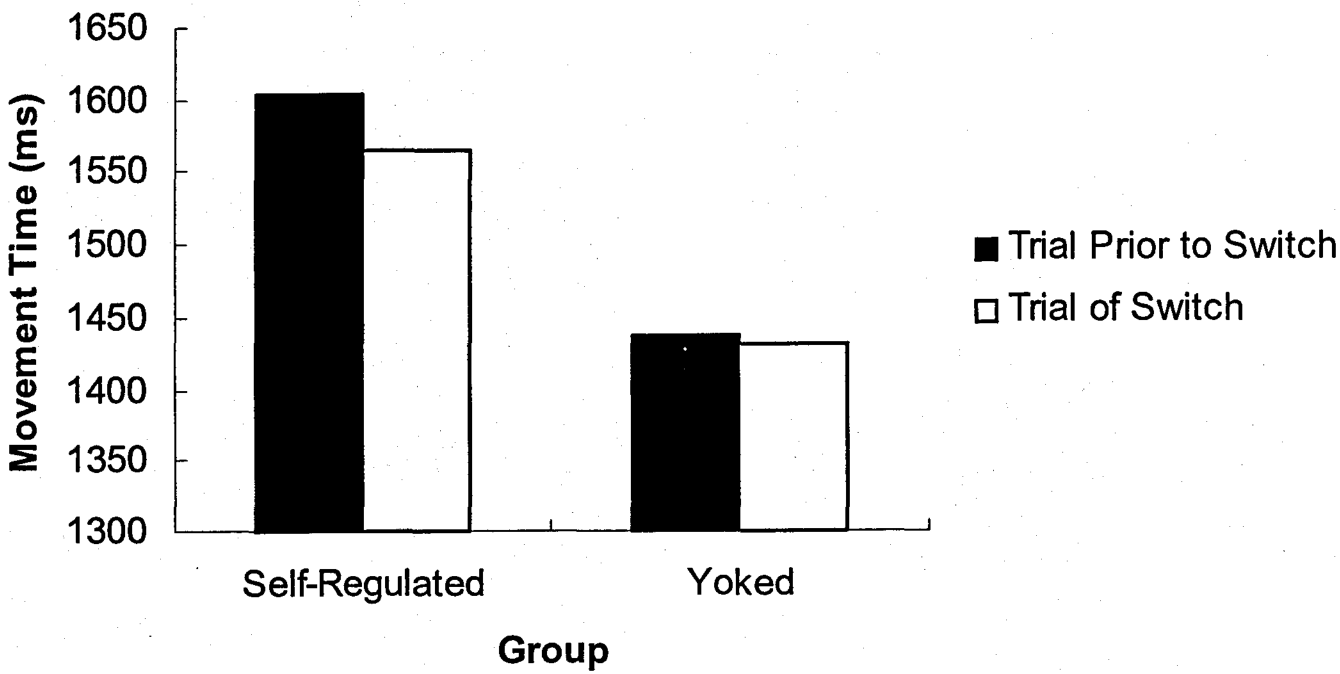

1400
1200
1000
800
600
400
200
0
Planning Time (ms)
Last Acquisition
Retention
Block
Blocked
Random
Self-Regulated
Yoked

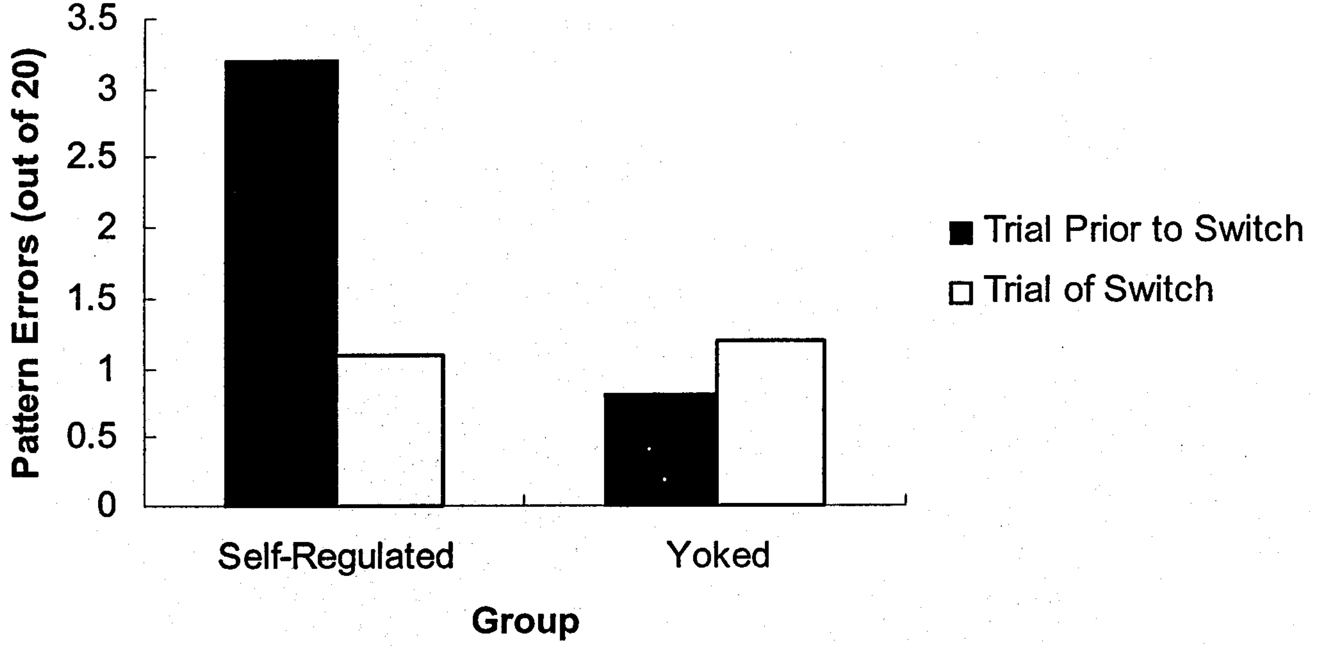

3
2.5
2
1.5
1
0.5
0
Cursor Errors (out of 20)
1 2 3 4 5 6 7 8
Easy
1 2 3 4 5 6 7 8
Hard
Task Complexity by Block
Blocked
Random
Self-Regulated
Yoked

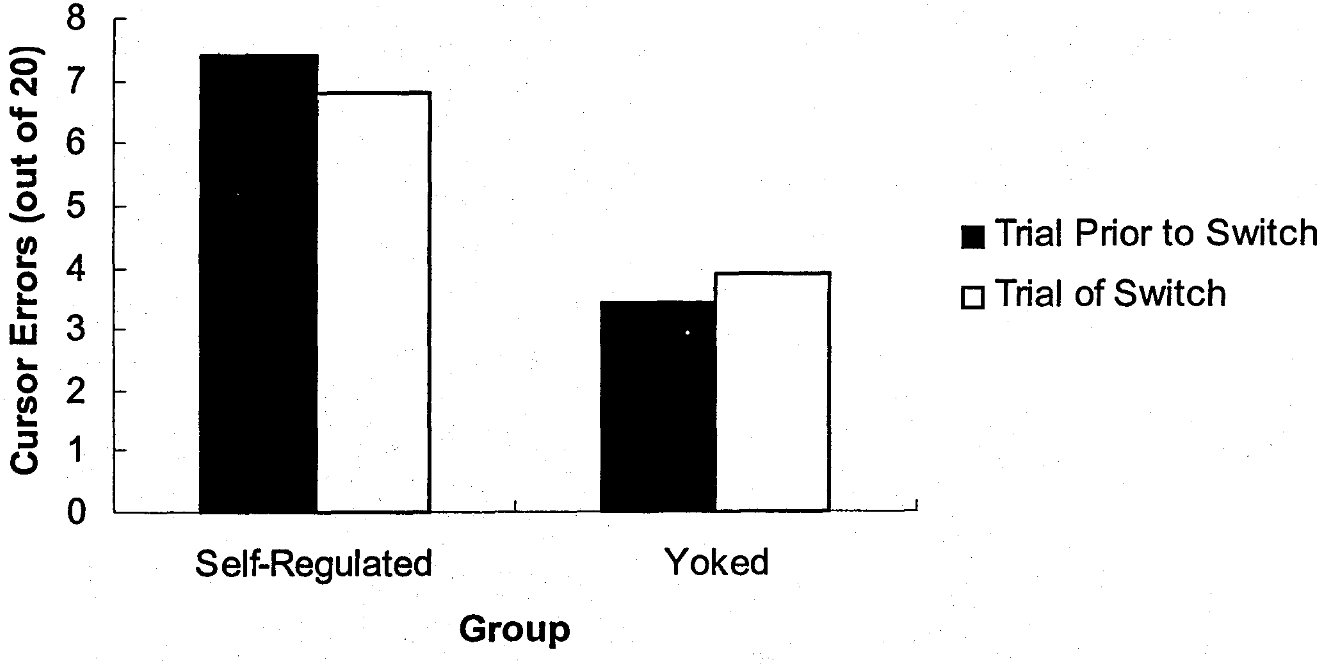


3.0
2.5
2.0
1.5
1.0
0.5
0.0
Cursor Errors (out of 20)
Last Acquisition
Retention
Easy
Last Acquisition
Retention
Hard
Blocked
Random
Self-Regulated
Yoked


3000
2600
2200
1800
1400
1000
Movement Time (ms)
Dominant
Non-Dominant
Hand
Easy
Hard


1650
1600
1550
1500
1450
1400
1350
1300
Movement Time (ms)
Self-Regulated
Yoked
Group
Trial Prior to Switch
Trial of Switch


3.5
3
2.5
2
1.5
1
0.5
0
Pattern Errors (out of 20)
Self-Regulated
Yoked
Group
Trial Prior to Switch
Trial of Switch


8
7
6
5
4
3
2
1
0
Cursor Errors (out of 20)
Self-Regulated
Yoked
Group
Trial Prior to Switch
Trial of Switch