AN EVALUATION OF THE AUTONOMY SUPPORT PREDICTIONS AND RECOMMENDATIONS IN OPTIMAL THEORY

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Abstract

Research in the field of motor learning focuses on how practice variables impact the retention of movement skill. The Optimizing Performance Through Intrinsic Motivation and Attention for Learning (OPTIMAL) theory is a modern and influential theory of motor learning, hypothesizing that three factors underlie optimal practice: autonomy support, enhanced expectancies, and an external focus of attention (Wulf & Lewthwaite, 2016). The purpose of this dissertation was to test the OPTIMAL theory predictions and recommendations related to the autonomy support factor as well as a key prediction about the relationship between practice performance and learning. Specifically, OPTIMAL theory predicts that providing autonomy support, usually by presenting learners with choices during practice, enhances a) expectancies for successful performance, b) motor performance during practice, and c) motor learning, as measured after at least a 24-hour delay. In addition, OPTIMAL theory predicts that, in general, conditions that enhance performance enhance learning. Emanating from these predictions are recommendations that instructors ask learners to choose when they receive feedback as well as when to practice specific skills in order to support their autonomy. These recommendations put OPTIMAL theory in conflict with previous theories of motor learning that predict certain feedback (guidance hypothesis) and practice schedules (schema theory) may be optimal for performance but suboptimal for learning. These conflicts were addressed by relying on the OPTIMAL theory prediction that instructionally-relevant choices, such as when to receive feedback, and instructionally-irrelevant choices, such as which colour golf ball to putt, each support autonomy and affect motor learning and performance similarly. In this way, it was possible to manipulate autonomy support, feedback schedule, and practice schedule independently, and test whether scheduling variables have an effect when learners have their autonomy supported. This dissertation tested the autonomy support predictions and recommendations in OPTIMAL theory by conducting two increasingly high-powered factorial experiments and a bias-corrected meta-analysis. In the first experiment, a total of 72 participants were assigned to one level of two independent variables: autonomy support (choice, yoked) and knowledge of results (KR) frequency (100%-KR, 50%-faded-KR). The experiment involved putting golf balls on an indoor putting surface with the goal of stopping the ball on a specific point on the green. Participants putted from behind a screen that occluded their vision of the outcome of their putts, forcing them to rely on augmented KR to learn to improve their putting accuracy. Baseline putting accuracy, expectancies, and autonomy measures were recorded and then participants completed ten blocks of five practice trials. Participants in the autonomy supportive conditions were asked to choose from three different colours of golf ball (green, yellow, red) for each putt during practice. Conversely, participants in the yoked conditions were matched to the golf ball colour schedule chosen by a counterpart in the autonomy support conditions. Participants also received KR pertaining to the final location of their putts. In the 100%-KR conditions, participants received KR following all 50 practice putts. Conversely, participants in the 50%-faded-KR conditions received KR after half of their practice putts, beginning with higher frequencies of KR that were gradually reduced across practice blocks. Following practice, participants completed autonomy and expectancy measures and then returned the following day to complete a retention test and a transfer test to a new, farther target than had been practised. The results displayed no statistically significant effects of autonomy support or feedback frequency on expectancies, learning, or performance. Due to the null results in Experiment 1, the power was substantially increased in Experiment 2. A total of *N* = 128 participants were assigned to one level of two independent variables: autonomy support (choice, yoked) and practice schedule (variable, constant). Participants practiced a dart throwing task with their non-dominant hand for 12 blocks of three darts. Participants in the autonomy support conditions were asked to choose from three colours of dart flight for each of their practice blocks, while their counterparts in yoked conditions followed the same dart-colour schedule. The variable practice conditions rotated among three different targets during practice, while the constant practice conditions threw all their darts to the central target. The day after practice, participants returned to perform a retention test to the central target and a transfer test to a previously unpracticed target. Following a pre-registered analysis plan, the results revealed that the autonomy support groups reported higher levels of perceived autonomy need satisfaction following practice. Further, the yoked groups performed significantly more accurately than the autonomy support groups, while there were no significant differences between groups at transfer. The constant practice conditions performed more accurately during practice, but less accurately during transfer than the variable practice conditions and the change in relative effectiveness from practice to transfer was significant. These results were inconsistent with OPTIMAL theory and call into question some of its central predictions. Critically, the basic prediction that autonomy support is beneficial to motor learning was not supported in either experiment. In order to evaluate the evidence that providing choice during practice is beneficial for motor learning, as well as the hypothesis that all choices are equally effective, a meta-analysis of the so-called self-controlled learning literature was conducted. Following a pre-registered plan, a search for all randomized experiments that met the following criteria was conducted: 1) A self-control group in which participants were asked to make at least one choice during practice, 2) a yoked-group that experienced the same practice conditions as the self-controlled group, 3) a delayed ~24-hour retention test or test with longer delay interval, 4) an objective measurement of motor performance, and 5) publication in a peer-reviewed journal or acceptance as part of a Master's or PhD thesis. A total of 79 experiments were identified that met the inclusion criteria but 23 were excluded because there were insufficient data to calculate effect sizes after contacting the authors. The resultant sample of *k* = 56 experiments were submitted to a naïve random effects model which estimated the average effect of self-controlled practice as *g* = .43. Publication status significantly moderated the self-controlled practice effect, accounting for 42.6% of the heterogeneity in the sample. While published experiments displayed a strong benefit of self-controlled practice, unpublished experiments found almost zero effect. To correct for selection based on statistical significance, a weight-function model was fit to the data with .025 one-tailed *p*-value cutpoint. Adjusting for selection provided a substantially better fit to the data and the adjusted estimated average effect size was *g* = .13 and not statistically significant. A suite of sensitivity and exploratory analyses were conducted and the results converged with the weight-function model estimate. Consistent with the OPTIMAL theory prediction, choice-type did not significantly moderate the effect of self-controlled learning. This finding was difficult to interpret however, as the more important finding of the meta-analysis was that the effect of self-controlled learning could not be distinguished from zero based on the available evidence.

Overall, the results of this dissertation contradict the OPTIMAL theory predictions and recommendations tested.

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Statement of Contribution

I, Brad McKay, was primarily responsible for the research program in this dissertation. I designed the studies, collected and analyzed the data, and wrote the articles, all under the guidance of my supervisor, Dr. Diane Ste-Marie. My thesis advisory committee consisted of Dr. Erin Cressman and Dr. Bradley Young and both individuals provided conceptual input at my thesis proposal and periodic committee meetings. I was assisted with participant recruitment and data collection by Nicholas Collard on Experiment 1. I received assistance with participant recruitment and data collection for Experiment 2 from several people: Kassandra Simcox, Alexandre Mir-Orifice, Finley Miller, Teanna Gauthier, Maggie Jeffery, Olivia Earl, Jameel Kara, Jules Jacobson, Annika Majcher, Janine Sibayan, Malick Turenne, Rachel Jones, Patricia Silva-Roy, Jessica Butterfield, Mary-Anne Vinh, Kayla Bernier, Elizabeth Rosochova, Matthew Carlson, Jessica Belenger, Jennifer Vo, Heather Smith, Kyla Bruni, Ariana Paul, Taylor Balhuizen-Hosmar, Abbigail Tremblay, and Lauren Shearer. I received assistance searching for articles, making inclusion-rejection decisions, and extracting data, all of which was done in duplicate, by Zachary Yantha, Julia Hussien, and Heather Smith. In addition, Zachary Yantha, Julia Hussien, and Michael Carter provided conceptual input on Study 3 and as such will be included as coauthors when the manuscript is submitted for publication. Finally, Dr. Diane Ste-Marie provided invaluable insight, editorial work, and conceptual contribution to every element of this dissertation and as such will be included as a coauthor on all articles submitted for publication.

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My journey was more difficult than expected. On a good day, it takes a village. But on a long, uncertain, at times impoverished trek that village was asked for more than they bargained. This journey would have ended, for better or worse, some time ago were it not for the excessive support of my closest allies. My dad, Wendell McKay, my mom, Barbara Betts, my partner Kassandra Simcox, and my supervisor Diane Ste-Marie were all more supportive than any reasonable prior, even for parents, partners, and certainly for supervisors.

My dad has been my best friend for years and we talked several times per week during my doctoral studies. We talked about every detail of my work. It takes patience and love to listen to meandering lectures about the distribution of *p*-values without any formal background in statistics. We've always learned together, whether on a baseball field or in the lab. When my undergraduate thesis involved 150 hours of data-collection, including dozens of hours of throwing batting practice with whiffle balls from 15 feet away and no protection, Dad was there for almost all of it. He brought a constant supply of Tim Hortons and threw batting practice while I snuck in a meal. He helped with taking measurements, judging balls and strikes for the post-tests, and scoring videos to assess inter-rater reliability. When I needed to come up with a task for my Master's thesis, dad found a whiffle ball pitching machine that was on budget. It worked better than I could have imagined. Every step of this journey, Dad has been my best friend and my hero. He caught me each time I fell and offered consistent support regardless the difficulties. Now that it's over I'm happy to look back and see so many more highs than lows

and bask in the satisfaction of accomplishing a dream that I shared with Dad, Mom, and many others.

Mom has always done anything humanly possible to help make sure I’ve achieved my goals. She helped make sure I went to university in the first place and once I’d found my calling she did anything she could to help make it easier. One time I couldn’t see my computer screen so Mom read me the assignment and typed my dictated answers to help me make a deadline. Mom was there for me through all the great moments, as well as the most difficult. One of the most impactful years of my doctorate was 2017,when we lost my grandfather Rex McKay and my grandmother Leona Betts. Both losses were painful but losing my grandmother was especially difficult for us. Mom and I worked really hard to get through the loss and the aftermath together. We supported one another in the most difficult times and managed to conquer our most challenging tests. I am really proud of my mother for her strength and character and am endlessly grateful for the love and support she gives me.

My wonderful partner Kassandra is the most supportive teammate I could ever imagine and most definitely more than I deserve. She was involved directly with the work in this dissertation: recruiting participants in both experiments, participating in early pilot runs of each experiment, installing the target in the second experiment, editing the formatting and references of this document, aggregating data, and engaging in hours of discussion about nearly every detail of the thesis. Beyond her extensive contributions to the project itself, Kassandra’s impact on daily existence was profound. She nurtured me through struggles and poor health and supported me in the most trying of times; always with a smile and warmth that made me want to keep going. I am so thankful for everything Kassandra has done to help make this dissertation a reality.

I don’t think it is ever easy to be a supervisor, but I do think it was especially difficult to be my supervisor. None of the experiments we conducted worked as expected… none even close, really. It was starting to feel like none of the research questions we considered addressing in a dissertation were going to be fruitful courses of action after five topics needed to be dropped. I became despondent. The entire endeavour seemed likely to fail at several points. But Diane would not give up on me or on the idea that I could and should finish this degree. I will be forever grateful to Diane for her above and beyond support and mentorship. I chose to work with Diane because I thought she was the role model for the type of professor I wanted to be, but I didn’t realize just how unattainably high she sets the bar. I will forever look at Diane as the epitome of what a professor should be.

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1. Chapter 1

General Introduction

This dissertation was intended to test and potentially extend a modern theory of motor skill learning and performance: Optimizing Performance Through Intrinsic Motivation and Attention for Learning (OPTIMAL) theory (Wulf & Lewthwaite, 2016). OPTIMAL theory has three factors, including attentional focus and expectancies, but the focus of this dissertation was on the most controversial factor (Carter & Ste-Marie, 2017a): Autonomy support. Autonomy support seemed a fruitful area for further investigation because a) autonomy support is recommended by Wulf and Lewthwaite in OPTIMAL theory as a solution to scheduling augmented feedback and practice variability (i.e., ask the learner to choose), two common motor learning variables otherwise unaddressed by OPTIMAL theory, and b) asking learners to choose their own augmented feedback and practice variability schedules means they may choose what other theories predict are suboptimal schedules, allowing for experiments that test between theories. For example, schema theory (Schmidt, 1975) predicts that repetitively practicing the same parameters of a task, known as constant practice, is less effective for learning than following a more variable schedule. Similarly, the guidance hypothesis (Salmoni, Schmidt, & Walter, 1984) predicts that receiving feedback after every practice trial is less effective than a reduced schedule of feedback. Asking learners to choose their own practice schedule could result in a constant practice, just as they may ask to receive feedback following each of their practice trials. Therefore, it seems the recommendations in OPTIMAL theory are in disagreement with two previously influential perspectives in motor learning.

Three experiments were planned for this project. In the first two experiments, autonomy support was crossed with augmented feedback schedule (Experiment 1) and practice schedule (Experiment 2) in factorial designs. These experiments afforded the opportunity to a) replicate the autonomy support effect previously reported only by the OPTIMAL theory authors, b) test between OPTIMAL theory and other influential theories (guidance and schema, respectively), and c) either confirm the OPTIMAL theory predictions or reveal opportunities to improve the OPTIMAL model by integrating aspects of the other theories.

The third experiment planned for this dissertation would have endeavoured to test an integrated OPTIMAL model against the theory in its present form, however as the reader will discover in more detail later in the document, the first two experiments failed to replicate the autonomy support benefit predicted by OPTIMAL theory. The second experiment was the most powerful investigation of autonomy support and motor learning to date and yet the results were significantly discordant with OPTIMAL theory. These results called into question the evidential value of the literature buttressing the autonomy support hypothesis while demotivating the initially planned third experiment. Therefore, instead of the third experiment, a meta-analysis was conducted to assess the evidential value in the self-controlled learning literature with a focus on correcting for selection biases (like publication bias and *p*-hacking). The meta-analysis revealed that the evidence for an overall self-controlled learning effect was significantly biased by selection effects around $p = .05$. The adjusted estimated effect size in the literature was small despite a high proportion of significant effects and a median $N = 36$. The *p*-curve analysis of experiments reporting significant results revealed evidence of *p*-hacking with the most commonly reported *p*-values residing between .04 and .05.

Collectively, the primary findings of this dissertation indicate that autonomy support does not enhance motor learning and performance in a meaningful way. These results have serious implications for motor learning research, a discussion taken up in the final chapter of this dissertation. In the following sections of this introductory chapter, the relevant extant literature is reviewed to situate the research questions in this dissertation within the greater context of motor learning research. Key concepts in motor learning are addressed first: What is a motor skill and how do we measure motor skill learning? Subsequently, the motor learning theories that were tested by this research are reviewed for the reader. Schema theory, the guidance hypothesis, and the primary focus of this work, OPTIMAL theory, are each reviewed in turn. Lastly, the rationale for the first two experiments in this project is outlined to prepare the reader to interpret the results described in Chapters 2 and 4.

1.1 Literature Review

1.1.1 Defining Motor Skill and Motor Learning

Jack Adams (1987) proposed three criteria for defining a skill: Behavioural complexity, that it is learned, and that it is goal-directed. A motor skill, therefore, can be defined as a complex, learned, goal-directed movement. Motor skill is thus broadly defined, and as such, so too is motor skill learning. A novice baseball player may learn the motor skill of ball-catching if after some practice he acquires a sustained ability to catch a ball that is thrown directly to him, when previously he routinely failed. Further, an intermediate baseball player may learn the motor skill of “pop-fly” catching if after some practice she develops the ability to regularly catch balls hit high into the sky when she previously failed at such a task. Finally, a professional baseball player may have learned to catch a ball at the highest level of performance if, after much practice, the player is able to find unique solutions to novel task demands when catching balls that have been hit or thrown. Motor skill learning, therefore, is not defined by having met a certain criterion of ability, but rather, dynamically, as the change in the ability to achieve a goal as a function of practice.

Change in the ability to achieve a goal as a function of practice is itself an ambiguous definition. How is "change in ability" defined? For example, Tango and colleagues (Tango, Lichtman, & Dolphin, 2014) report that a professional baseball batter performs better each time he faces the same opposing pitcher in the same game – independent of fatigue effects suffered by the pitcher. However, while professional batters improve their ability as a function of practice within the same game, there is no evidence that they fare better each successive game that they face the same pitcher (Tango et al., 2014). Thus, professional batters experience a transient change in their ability to achieve their goal each time they face a pitcher in the same game, but do not experience a relatively permanent change in ability. Is the transient, in-game change in ability an example of motor skill learning? Many motor skill learning researchers would say no (e.g., Schmidt & Lee, 2004; Salmoni, Schmidt, & Walter, 1984). Kantak and Winstein (2012) review evidence that motor skill learning involves a relatively permanent change in ability which is distinct from same-day or same-session changes in performance that are not sustained in future sessions. In this case, "relatively permanent" is defined as lasting at least one day[1]. In their review, Kantak and Winstein reported that experiments which measured performance immediately following practice and again 24 hours later frequently observed different effects at each time point. Most frequently, group differences were not observed immediately after practice, but differences would emerge after

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[1] Permanent seems a poor word choice, but is the one most frequently used in the literature. The relative nature of this permanence is with respect to practice performance.

a 24-hour delay. In a few cases, the direction of the group differences changed from the immediate test to the 24-hour delayed test, a result commonly described as a ‘reversal effect.’ Delayed effects and reversal effects provide evidence that practice variables can impact motor performance distinctly at different time points. If learning is defined as a relatively permanent change in ability, then it seems important to measure motor learning after a delay of at least 24 hours since the effect of practice variables can change over that period.

A 24-hour delayed retention or transfer test has become popular in motor skill learning experiments and research on motor memory consolidation provides support for this practice. Motor memory consolidation is defined as a set of processes that occur after practice which allow the memory representation of the movement to become more stable (Robertson, 2004). There are two broad types of memory consolidation processes: Offline learning and memory stabilization. Offline learning involves an improvement beyond the level of performance observed during practice after some period of abstaining from the task (Robertson, 2004, 2009; Robertson, Press, & Pascual-Leone, 2005). Memory stabilization refers to an increased resistance against retroactive-interference from practicing a new task subsequent to the learning of a primary task. Researchers, for example, have observed retroactive-interference when participants have practiced a new task within 4 hours of a primary task, while delays of 4 to 8 hours between practicing tasks has avoided such interference effects (Shadmehr & Holcomb, 1997; Kantak & Winstein, 2012; Trempe, Sabourin, Rohbanfard, & Proteau, 2011). Additionally, offline learning may be, in part, sleep-dependent. Studies by Walker and colleagues (Walker, Brakefield, Morgan, Hobson, & Stickgold, 2002; for a review: Walker & Stickgold, 2004) suggest that sleep, particularly stage 2 non-REM sleep late at night, plays a critical role in offline learning. Further, sleep may also facilitate motor memory stabilization and prevent retroactive-interference (Korman, Doyon, Doljansky, Carrier, Dagan, & Karni, 2007). The importance of a temporal delay following practice for motor memory consolidation, and in particular the putative role of sleep, highlights the need to measure motor skill learning after at least a 24-hour delay.

Motor skill learning researchers have not always measured learning after a 24-hour delay (Bilodeau & Bilodeau, 1961; Adams, 1987; Salmoni et al., 1984). Consider the long history of research focused on knowledge of results. Knowledge of results (KR) refers to outcome details that are made available by an external source following execution (Salmoni et al., 1984). Since the early 1900's, researchers have considered KR a critical variable for motor learning (Adams, 1987; Judd, 1905). For example, 114-years-ago, Judd (1905) reported an absence of improvement during practice when KR was not provided to the participant. By 1961, it was considered established that "there is no improvement without KR, progressive improvement with it, and deterioration after its withdrawal" (Bilodeau & Bilodeau, 1961, p.251). As delayed retention tests became more commonly used, the temporary effects of KR on performance could be distinguished from more stable learning effects. Salmoni, et al. (1984) first predicted that learning, as measured by a delayed no-KR retention test, would be enhanced by practicing with a reduced frequency of KR, while increased frequencies of KR would have beneficial, but temporary, effects on performance. Subsequent to publication of what is now known as "the guidance hypothesis" (Salmoni et al., 1984), numerous experiments have observed a learning advantage with a reduced relative frequency of KR (e.g., Nicholson & Schmidt, 1991; Guadagnoli & Kohl, 2001; Lee, White & Carnahan, 1990; Sullivan, Kantak, Burtner, 2008;

Winstein, Pohl, & Lewthwaite, 1994; Bruechert, Lai, & Shea, 2001; Wulf & Schmidt, 1989; Wulf, Schmidt, & Deubel, 1993; Wulf, Lee, & Schmidt, 1994; Lai & Shea, 1998; Winstein & Schmidt, 1990; Wulf & Schmidt, 1989). Although our understanding of KR and motor learning continues to evolve (Wulf & Lewthwaite, 2016), the shift to 24-hour delayed retention and transfer tests caused what Kant (1781) may have called a “Copernican revolution” in motor learning thinking: A reversal from concluding high frequency KR is optimal for motor learning to concluding the opposite.

In the past three decades, 24-hour delayed retention and transfer tests have become the standard indices of learning in what can be considered the “information processing,” and “social-cognitive” motor learning traditions (Salmoni et al., 1984; Schmidt, 1975; Wulf & Lewthwaite, 2016). In line with these traditions, the experiments conducted in this dissertation measured motor learning with 24-hour delayed retention and transfer tests.

In the following sections, the traditional information processing motor learning theories that were tested against OPTIMAL theory are reviewed: Schema theory and the guidance hypothesis.

1.2 Schema Theory

Richard Schmidt published the seminal Schema Theory in 1975, inspiring decades of experimental work thereafter. The schema theory consists of three primary elements: The Generalized Motor Programme (GMP), recall schema, and recognition schema. From these elements emerge a number of predictions about motor learning and performance, and while not every prediction has been supported, many of the ideas continue to invigorate research today (e.g., Stuhr, Hughes, & Stockle, 2017).

Schema theory (1975) attempted to overcome two key problems unaddressed by Adam's Closed-Loop Theory (1971): The novelty problem and the storage problem. Adam's theory hypothesized a one-to-one mapping of motor programmes and feedback to motor responses, but Schmidt argued this led to what he called the "storage problem." The storage problem was that the number of different motor programmes required to control the nearly infinite flexibility of the human motor system would be too numerous for the central nervous system to store. Schmidt's solution to the storage problem was a central tenet of Schema Theory: the generalized motor program (GMP), a scalable code for movements of a particular class that can accommodate a range of parameters. Since the GMP can be scaled, it codes for more than one specific movement, requiring much less storage capacity.

The novelty problem was also a challenge for motor learning theories that presumed a one-to-one ratio of motor programmes to movements. If a motor programme is required to execute a given movement, how does one complete a task for the first time? In Schema Theory, the GMP for current movements could be extended to novel situations via two scaling parameters (time and amplitude), and in Schmidt's view (2003) this provided a solution to the novelty problem that previous theories had failed to address.

According to schema theory, the GMP is the central preplanning of invariant features of a class of movements, not the specific efferent signals produced to actualize movement (Schmidt, 1975). It was proposed that there were three invariant features of the GMP: The sequence of events (Shea & Wulf, 2005), the relative timing, and the relative forces of a given movement class (Schmidt, 1975). To illustrate, consider the act of throwing a ball. The arm will always move backward preceding its forward movement (invariant order), the countermovement will always have a longer duration than the forward movement (invariant relative timing), and the countermovement will always be relatively less forceful than the forward movement (invariant relative force). The putative GMP for a throw could thus be adjusted to new targets, or intentions, by scaling the invariant features of the movement.

The proficiency with which individuals adjust their GMPs to accommodate new task demands was argued to be a function of two memory states: the recall schema and recognition schema (Schmidt, 1975). The schemata were proposed to be abstract representations of past movement attempts and their outcomes with respect to the movement goals. While the memory of a specific movement was purported to fade quickly, the memory of the movement schema was theorized to persist and faded slowly (Schmidt, 1975).

The recall schema was proposed to control movement specifications and consists of three pieces of information: The initial conditions of a movement, the response specifications of the GMP, and the outcome of the motor response (Schmidt, 1975). The recognition schema was proposed to store the initial conditions of the movement and its outcome as well, but instead of the response specifications of the GMP the recognition schema was proposed to store the sensory consequences of a given action. Thus, according to schema theory, the recall schema is responsible for response production while the recognition schema drives error detection and correction. It was hypothesized that both schemata pair previous movements with their outcomes, similar to the way a regression line is fit between two variables. By matching previous movement parameters (for example, absolute force), or sensory consequences (the feeling associated with a forceful shot) with previous outcomes (a basketball shot in the net), recall and recognition schemata were thought to allow a performer to produce an effective response in a novel situation, whether within the range of previous experience (by interpolation) or beyond the range (by extrapolation). Thus, a basketball player may produce an accurate shot from areas on the court they had not shot from before, including long range or acrobatic shots that are outside the range of previous experiences.

From the ‘regression line analogy’ follows a central prediction of Schema Theory: Practicing movements that share the same GMP with a variety of intended parameters will enhance motor learning, as reflected by absolute error on a delayed no-KR retention test (Schmidt 1975). Increasing the variety of parameters during practice has become known as variable practice and can be viewed in contrast to practicing a skill with the same parameters repetitively, known as constant practice (Schmidt & Wrisberg, 2008). The predication that variable practice is more effective than constant practice has been supported in several experiments (Newell & Shapiro, 1976; McCracken & Stelmach, 1977; Lee, Magill & Weeks, 1985; Wrisberg, Winter, & Kuhlman, 1987; Del Rey, Wughalter, & Whitehurst, 1982; Barto, 1986, Experiment 1; Bird & Rikli, 1983; Shea, Lai, Wright, Immink, & Black, 2001; Giuffrida, Shea, & Fairbrother, 2002; Catalano & Kleiner, 1984; Husak & Reeve, 1979; Wrisberg & McLean, 1984; Wrisberg & Ragsdale, 1979; Clifton, 1985; Wrisberg & Mead, 1983; Kerr & Booth, 1978; Moxley, 1979; Pigott & Shapiro, 1984; Kelso & Norman, 1978; Smultkis, 1981; Poretta, 1982; Kantak, Sullivan, Fisher, Knowlton, & Winstein, 2010; 2011).

Variable practice predictions notwithstanding, Schema Theory has not been entirely successful. For example, the relative forces within a GMP are not necessarily invariant (Schmidt, 2003; Schmidt & Mcgown, 1980). In one example, movements in horizontal and vertical planes are differentially affected by gravity, inconsistent with the invariant relative force prediction (Schmidt & Mcgown, 1980). Schema theory also omits an explanation for a number of results that succeeded its publication. For example, a number of findings in the social-cognitive tradition of motor learning cannot be accounted for by the Schema Theory of motor learning. Observational learning (Ste-Marie et al., 2011) is a challenge for Schema Theory, for example, because it provides no mechanism for motor learning without action. The potential motivational impacts of variables like choice or expectancies also fail to be accounted for by Schema Theory (Wulf & Lewthwaite, 2016). In a classic 'post-mortem' of Schema Theory, Schmidt (2003) lamented that the field needed a new theory, one that can account for the phenomena that Schema Theory successfully predicted, while improving on the areas it was deficient. Wulf and Lewthwaite (2016) make a similar claim regarding the need for a new theory in their OPTIMAL Theory, which will be described in detail in a later section of this chapter.

1.3 Guidance Hypothesis

Within the same tradition as Schema Theory, Salmoni and colleagues (1984) proposed a pre-theoretical account of KR and motor learning: The Guidance Hypothesis. While the Guidance Hypothesis was distinct from Schema Theory, both ideas were grounded in the cognitivist, information processing tradition. The Guidance Hypothesis predicted that KR has such a powerful influence on motor performance that learners come to rely on it. Thus, Salmoni and colleagues argued that providing learners with relatively lower frequencies of KR would enhance their learning by allowing learners to error detect and correct without becoming reliant on verbal feedback. Indeed, the primary prediction of the Guidance Hypothesis, that relatively less frequent KR is more effective for learning, has been supported in numerous experiments (e.g., Nicholson & Schmidt, 1991; Guadagnoli & Kohl, 2001; Lee, White & Carnahan, 1990; Sullivan, Kantak, Burtner, 2008; Winstein, Pohl, & Lewthwaite, 1994; Bruechert, Lai, & Shea, 2001; Wulf & Schmidt, 1989; Wulf, Schmidt, & Deubel, 1993; Wulf, Lee, & Schmidt, 1994; Lai & Shea, 1998; Winstein & Schmidt, 1990; Wulf & Schmidt, 1989). Further, a number of secondary predictions have also received ample empirical support since the Guidance Hypothesis' publication. For example, asking learners to estimate their errors prior to receiving KR has led to more effective learning when receiving high frequency KR (Guadagnoli & Kohl, 2001). Implementing a trial delay method, wherein KR is provided for a given trial only after a number of subsequent trials have been completed (Anderson, Magill, Sekiya, & Ryan, 2005), or providing KR as a summary of multiple trials (Schmidt, Young, Swinnen, & Shapiro, 1989) have both been reported to enhance learning while potentially decreasing acquisition performance. Finally, a number of studies have shown a similar pattern of results when manipulating knowledge of performance (KP) instead of KR (e.g., Weeks & Kordus, 1998); consistent with the speculation by Salmoni and colleagues that KR and KP may function via similar mechanisms.

Contemporary opinions on the tenability of the Guidance Hypothesis as an explanation of the role of KR on motor learning are mixed. Magill and Anderson (2013) reviewed the extant literature and concluded the evidence suggested the Guidance Hypothesis is a robust explanation for the role of augmented feedback. Conversely, Wulf and Shea (2004) noted a number of findings that appeared inconsistent with the guidance view. For example, two experiments by Guadagnoli, Dornier, and Tandy (1996) suggest that task complexity or difficulty moderates the effect of KR schedule. If receiving frequent KR prevents the learner from utilizing their own, intrinsic sources of feedback for error detection and correction, why would task difficulty interact with this process? In another example, Wulf and colleagues (Wulf, McConnel, Gartner, & Schwartz, 2002) manipulated the direction that augmented feedback cued the learner's attention, either toward their own body, called an internal focus of attention, or toward the effect of their movement, called an external focus of attention. When the feedback directed the learner's attention internally the results were consistent with the Guidance Hypothesis: Reduced relative frequency of feedback was most effective for learning. However, when the feedback cued learners to adopt an external focus of attention, a higher frequency of feedback was more effective for learning. Wulf, Chiviacowsky, Schiller, and Avila (2010) replicated the Attentional Focus X Feedback Frequency interaction with children learning a soccer throw in. Although the Guidance Hypothesis does not predict an interaction between feedback frequency and direction of attention, the experiments that have found this relationship have studied KP and not KR. Thus, while the speculation that KR and KP function via similar mechanisms may not hold, the primary prediction of the Guidance Hypothesis is not addressed by experiments studying KP.

Wulf and Lewthwaite have recently (2016; 2017) argued that the Guidance Hypothesis and Schema Theory fail to account for a variety of findings in the extant motor learning literature, in particular motivational influences, in addition to attentional influences, on learning and performance. For example, it is unclear how Schema Theory can account for the benefit of allowing a learner to choose whichever practice schedule they prefer, including a constant schedule, relative to asking the learner to follow an imposed schedule (e.g., Wu & Magill, 2011). Likewise, it is unclear how the Guidance Hypothesis can account for the benefit of choosing a feedback schedule, relative to receiving feedback on the same schedule without choosing (e.g., Janelle, Barba, Frehlich, Tennant, & Cauraugh, 1997). Wulf and Lewthwaite (2016) argued the inability of past theories to account for newer results in the motor learning literature creates the need for a new theory, positioning OPTIMAL Theory as a response to the failure of past theories to account for all relevant data. In the following section, the OPTIMAL Theory of motor learning and performance will be reviewed in detail.

1.4 OPTIMAL Theory

Gabriele Wulf and Rebecca Lewthwaite (2016) proposed the OPTIMAL Theory of motor learning and performance, an elegant theory of motor learning that includes three primary factors: 1) Expectancies, which refer to beliefs regarding future performance outcomes that can be enhanced or depressed, 2) Attentional focus, which refers to the mental focus of the learner that can be internally or externally directed, and 3) Autonomy, referring to a basic psychological need proposed by Self-determination theory (Deci & Ryan, 2000) that can be supported or thwarted. Each factor can be beneficial or deleterious to motor learning and performance and combining the factors has as additive effect (e.g., Wulf, Lewthwaite Cordozo, & Chiviacowsky, 2018). The basic overview of the theory is provided in Figure 1 and while it provides a general description of OPTIMAL Theory, it is not a comprehensive one. Nevertheless, the schematic in Figure 1 is a useful depiction of the proposed relationships among autonomy, expectancies, and attentional focus. All three factors are predicted to influence goal-action coupling – the cognitive fusion of intention and required action proposed to support automaticity – thereby modulating the ratio of task-focus and self-focus and in turn impacting performance and subsequently learning. Autonomy support is also predicted to enhance expectancies, which in turn enhance performance and learning as well.

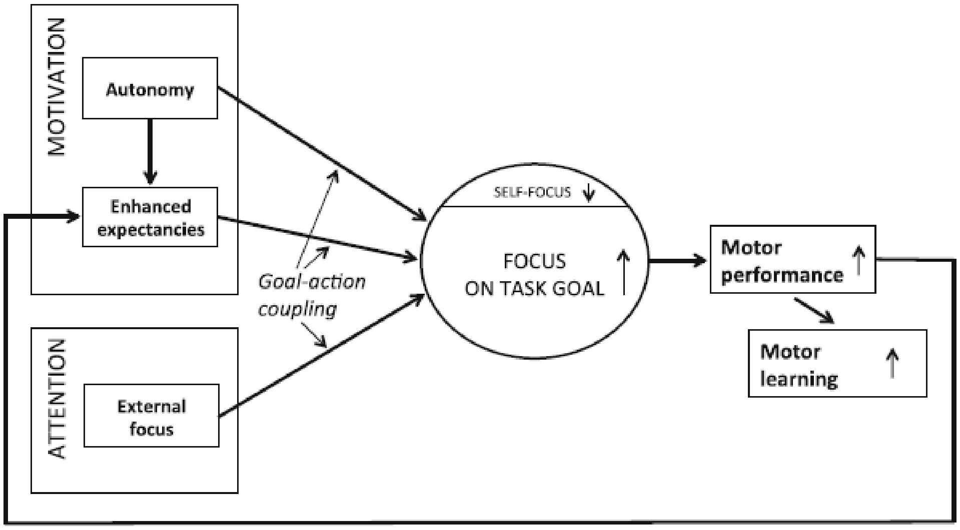

Figure 1.1. Schematic of the OPTIMAL Theory, from Wulf & Lewthwaite (2016, pp. 1391)

1.4.1 Attentional focus

The attention predictions of OPTIMAL Theory place emphasis on where a learner or performer should focus their mental attention in order to optimize their motor performance outcomes. A large body of evidence suggests that focusing on the intended outcome of an action is more effective than focusing on the specific movements required to achieve the desired outcome (for a review see Wulf, 2013). In OPTIMAL Theory nomenclature, focusing on the intended outcome of a movement is referred to as an external focus of attention, while focusing on the specific movements involved is referred to as an internal focus. An external focus of attention has been observed to enhance motor learning and performance in a number of dimensions. First, an external focus may enhance movement effectiveness. For example, improved balance performance (McNevin, Shea, & Wulf, 2003), golf shot accuracy (Bell & Hardy, 2009), dart throwing accuracy (Lohse, Sherwood, & Healy, 2010), and ball throwing accuracy (Chiviacowsky, Wulf, & Avila, 2013) have all been observed with an external focus relative to an internal focus. Second, an external focus may increase movement efficiency. For example, reduced electromyography (EMG) activity has been observed in conjunction with greater force production, indicative of more efficient performance (Marchant, Greig, & Scott, 2009). Third, external focus may enhance the acquisition of intended movement form. Wulf and colleagues (2010) observed improved soccer throw-in form, as judged by expert ratings, when feedback directed attention to the intended effects of the form, rather than the specific movements themselves. Fourth, motor automaticity has been enhanced by an external focus. In one study, participants learned to balance on a stabilometer while focusing on either their feet or the platform. Participants instructed to adopt an external focus were later able to respond to a secondary probe reaction time task more quickly than participants with an internal focus (Wulf et al., 2001). The authors concluded that the balance task was executed via more automatic control mechanisms, freeing up attentional resources to perform the reaction time task, results that have been replicated elsewhere (e.g., Kal, van der Kamp, & Houdijk, 2013).

In order to account for the varied benefits of an external focus of attention, Wulf and Lewthwaite (2016) propose two mechanisms underlying the benefit of external focus on motor learning and performance: First, by directing attention to the task goal, and second, by reducing focus on the self. An external focus of attention is therefore considered an important contributor to goal-action coupling, the hypothesized cognitive fusion of action to intended outcome. The authors highlight evidence that self-referential cognitive behaviour may be the brain's default mode (Brewer, Worhunsky, Gray, Tang, Weber, & Kober, 2011). Self-referential processing may encourage conscious control mechanisms which interfere with the more automatic control processes that are the hallmark of skilful movement. In this view, instructing an external focus of attention is needed to overcome the default tendency to focus internally. Thus, instructing an internal focus is often no worse than no instructions, but when the participants already utilize automatic control processes an internal focus can be detrimental (Wulf, 2013).

1.4.2 Expectancies

Wulf and Lewthwaite (2016) define expectancies as personal beliefs regarding what is about to occur. Unlike Bandura's Social Learning Theory (1989), expectancies are defined broadly in OPTIMAL Theory and include both self-efficacy beliefs as well as outcome expectancies. In fact, self-efficacy is described as a "particularly pertinent" form of expectancy due to OPTIMAL Theory's focus on volitional movement (Wulf & Lewthwaite, 2016). In addition to self-efficacy and outcome expectancy, OPTIMAL Theory expectancies also include confidence and, potentially, collective efficacy. Collectively, expectancies are posited to have beneficial effects on learning and performance when they are somehow increased.

Although OPTIMAL Theory expectancies are a broad category of variables of which self-efficacy is a specific example, Bandura's self-efficacy (1989) theory has informed many experimental manipulations employed to enhance or depress participants' expectancies.

According to Bandura, there are four sources of information that influence an individual's self-efficacy beliefs: Personal mastery experiences, vicarious mastery experiences (particularly when the observed other is considered by the observer to be similar), verbal persuasion, and physiological response. Researchers have manipulated these sources of information, in particular the first three, in efforts to modulate participants' expectancies and test the effect of those modulations on subsequent learning and performance. In the following paragraphs, examples of these manipulations and their impacts on motor learning and performance will be discussed.

One experimental manipulation of expectancy that has been used frequently is non-veridical feedback. Non-veridical (or 'bogus') feedback can, in theory, manipulate a participant's personal mastery experience by convincing them they performed more, or less, effectively than what actually occurred. For example, a study by Hutchinson and colleagues (Hutchinson, Sherman, Martinovic, & Tenenbaum, 2008) asked participants to complete an isometric grip endurance test using a hand dynamometer and provided either positive, negative, or no non-veridical feedback following the first trial. Participants were asked to maintain 25% of their maximum voluntary contraction (MVC) for as long as possible while the experimenter provided concurrent feedback as to whether the grip force was at the target level. Following the first trial, participants were told their endurance was in the 90th percentile of the population, the 10th percentile of the population, were not provided bogus social comparative feedback, or were not provided feedback at all. Participants then completed a second trial of the same task, in addition to a self-efficacy measure. The results indicated that participants who received bogus feedback suggesting they performed in the 90th percentile subsequently maintained their grip at 25% of their MVC for significantly longer than participants who received feedback that they were in the 10th percentile or who did not receive feedback at all.

Subsequent studies have found that positive non-veridical social comparison feedback increased motor skill learning and performance as well (e.g., Montes, Wulf, & Navalta, 2018; Wulf et al., 2017; Chua, Wulf, & Lewthwaite, 2018). For example, Lewthwaite and Wulf (2009) conducted an experiment wherein learners received veridical KR plus a non-veridical “norm” for performance on that trial with that particular balance task. Participants who received non-veridical social comparative feedback suggesting they performed 20% better than average outperformed participants who did not received social comparative feedback and learners who were told they performed 20% worse than average on a subsequent retention test. Importantly, participants receiving bogus feedback also reported believing that feedback reflected their relative proficiency at the balance task, suggesting their expectancies were altered by the feedback.

Bogus feedback can mislead a person into believing they were successful at a given task when they were not. Providing different criteria for “successful performance” can manipulate an individual’s personal mastery experience as well. For example, in a study of visuomotor adaptation, Trempe, Sabourin, and Proteau (2012) observed that participants learned a new internal model more effectively, as represented by performance on a delayed retention test, when they practiced the task with a relatively easy objective compared to practicing with a difficult objective. Similar effects were observed when participants learning a coincident-timing task were provided with difficult or easy definitions of success (Chiviacowsky, Wulf, & Lewthwaite, 2012). Importantly, participants who experienced the easier definition of success reported higher self-efficacy for the task, perhaps indicating that enhanced expectancies facilitated more effective motor learning.

Personal mastery experience can be manipulated in typical motor learning experiments by adjusting the definitions of success or by providing non-veridical feedback suggesting successful or unsuccessful performance. Vicarious mastery experiences involve an individual observing someone else having success with a task, causing them to increase their own expectation for success. The distinction between a personal mastery experience and a vicarious mastery experience has been blurred by research investigating feedforward self-modelling (Ste-Marie, Vertes, Rymal, & Martini, 2011). Feedforward self-modelling involves recording several performances and splicing together the most successful instances to produce a video of an individual performing at a level superior to what they are currently capable (Dowrick, 2012). The individual then watches the feedforward video of themselves, providing the opportunity for vicarious *personal* mastery. In one study, participants exhibited more successful post-test performance if they were given the opportunity to watch their feedforward videos than a group of controls who did not have access to a feedforward video (Ste-Marie et al., 2011). Although watching feedforward videos seemed to impact performance measures, self-efficacy measures revealed no significant effects. Nevertheless, the Wulf and Lewthwaite cite feedforward video observation as a method for enhancing expectancies (2016, pp. 1386).

Verbal persuasion is another method to experimentally manipulate participant expectations. In one study (McKay, Lewthwaite, & Wulf, 2012), participants were asked to fill out a battery of questionnaires they were later told either: a) were well-validated measures that predict performance in high pressure situations (and the participants were told they scored 3 SD above the population average), or b) that the questionnaires were being tested to determine if they predict high pressure performance (no specific feedback was given regarding their scores on the questionnaires). Participants who were persuaded they were likely to do well above average in high pressure situations performed significantly more accurately on a high pressure throwing task than the group who were not given a non-veridical boost to their expectancies. In this study, self-reported confidence following the verbal persuasion manipulation correlated with subsequent high pressure performance.

In summary, non-veridical feedback and feedforward information, arbitrary definitions of success, and verbal persuasion have been found to modulate expectancies and influence motor learning and performance. Wulf and Lewthwaite (2016) argued that expectancies influence motor learning and performance through five hypothesized mechanisms. First, they suggest that increased expectancies serve a task-readying function. In this view, anticipating more positive outcomes may increase a person's readiness to act. Potentially this task-readying function can increase effort, alter perception of task-demands, and pre-movement excitation or inhibition. Second, enhanced expectancies were posited to enhance positive affect, which was purported to potentially facilitate learning and performance. The link between positive affect and motor behaviour is tenuous; however, there is limited evidence for a positive association between skilled performance and positive affect (see Lemos, Wulf, Lewthwaite, &

Chiviacowsky, 2017). Third, Wulf and Lewthwaite suggest that enhanced expectancies may influence attention and memory. For example, if a person is more confident in their ability to achieve an intended outcome, they may be less likely to adopt an internal focus of attention and self-monitor their movements. (Masters & Maxwell, 2008). Fourth, Wulf and Lewthwaite presented the idea that enhanced expectancies may cause a dopaminergic response, similar to what has been observed when learners are provided extrinsic rewards (Schultz, 2013). This argument highlights the difference between enhanced expectancies in OPTIMAL Theory and outcome expectancies in Social Learning Theory (Bandura, 1989): In OPTIMAL Theory, expectancies may be enhanced by increasing the expected reward for a given action or by enhancing an individual's belief in their ability to accomplish a given action. Wulf and Lewthwaite propose that triggering a dopaminergic response both facilitates performance and enhances learning, but recognized that this hypothetical relationship is likely complex. Fifth, Wulf and Lewthwaite reason that enhanced expectancies may help learners cognitively fuse their goals with their intended actions. In OPTIMAL Theory, this hypothesized process is called goal-action coupling.

1.4.3 Autonomy

Many researchers argue that a feeling of autonomy or volition is a basic psychological need (e.g., Deci & Ryan, 2008). Having the opportunity to exercise a choice, even when trivial, may increase an individual's intrinsic motivation (e.g., Eitam, Kennedy, & Higgins, 2013). Wulf and Lewthwaite (2016) argue that providing a choice can enhance motivation, which in turn enhances motor learning and performance. Nearly all of the evidence cited in the OPTIMAL Theory to support the relationship between autonomy and motor behaviour comes from a body of literature collectively referred to as self-controlled learning (McKay, Carter, & Ste-Marie, 2014; Sanli, Patterson, Bray, & Lee, 2013). In the typical self-controlled learning experiment, participants are divided into two groups: One with a choice over an aspect of their practice environment (most frequently KR), and one without a choice, who are instead yoked to the choices of their self-controlling counterparts. Numerous experiments have found that learners who have been provided with a choice over their practice environment perform and learn more effectively than learners who have been yoked to a counterpart's choices (McKay et al., 2014).

Many researchers have argued, in line with Wulf and Lewthwaite, that self-controlled learning is more motivating for the learner, and therefore motivation is largely responsible for the effectiveness of providing learners with a choice (for a review: Sanli et al., 2013). However, some authors have argued that non-motivational mechanisms are more likely causing the effect (Carter et al., 2014; Carter & Ste-Marie, 2017a, Carter & Ste-Marie, 2017b; Grand, Lohse, & Miller, 2017). Since most self-controlled learning experiments ask learners to control an aspect of their practice that is considered informative and important to their learning (KR, for example), it is difficult to determine whether motivation or other information processing processes are responsible for the typical benefit of choice. Lewthwaite and colleagues (Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015) have argued that asking a learner to control their feedback makes it difficult to infer the motivational effect of choice, since KR is informative and learners may choose to request KR when it would be most useful. As such, Lewthwaite and colleagues argued that a stronger test of the motivational impact of choice on motor learning and performance can be conducted by asking learners to make choices about features of their practice environment that are not instructionally-relevant. In one experiment, participants were asked to choose the colour of their golf ball for a golf putting task, while another group were yoked to their colour choices. While it is difficult to imagine why choosing a golf ball colour would be beneficial from an information processing perspective, instructionally-irrelevant choices have been shown to be intrinsically motivating (Patall, Cooper, & Robinson, 2008). The results of the experiment showed that learners who were asked to choose their golf ball colour learned to putt more accurately than their yoked counterparts. A number of subsequent experiments have replicated the benefit of providing learners with an instructionally-irrelevant choice (e.g., Wulf, Chiviacowsky, & Cordozo, 2014; Wulf, Iwatsuki, Machin, Kellogg, Copeland, & Lewthwaite, 2017). While it is difficult to explain the benefit of instructionally-irrelevant choices through an information processing lens, the motivational benefit of choice seems to fit these findings well. The experiments in this dissertation leveraged these less ambiguous effects of instructionally-irrelevant choices as a manipulation of autonomy support.

The OPTIMAL Theory includes three direct mechanisms through which autonomy may enhance motor learning and performance. They are increased self-regulatory responsiveness to errors, increased dopaminergic response, and performance facilitation. The first two mechanisms rely on scant evidence, currently, and the third mechanism, performance facilitation, is ostensibly tautological. The OPTIMAL Theory also includes a potential indirect mechanism for the benefit of autonomy, whereby it increases expectancies. Although the notion of a basic psychological need for autonomy is grounded in self-determination theory (SDT; Deci & Ryan, 2008), the specific mechanisms proposed for autonomy support in OPTIMAL theory are distinct from those proposed in SDT. First, autonomy support is predicted to enhance expectancies in OPTIMAL theory while being considered unrelated in SDT. Second, autonomy support is proposed to share the same underlying mechanism as extrinsic and controlling motivation in OPTIMAL theory, including a dopaminergic response, while autonomy support is thought to facilitate the adoption of self-determined motivation in SDT, which specifically differs from extrinsic motivational mechanisms.

1.4.4 Two cycles

The three factors discussed above – expectancies, attentional focus, and autonomy – are described in the OPTIMAL theory as either enhancing or impeding optimal learning and performance in self-reinforcing ways (Figure 2). In what the authors call the virtuous cycle, successful performance follows from conditions that heighten expectancies, direct an external focus, and support autonomy. Successful performance is predicted to trigger a dopaminergic response, which is hypothesized to enhance learning and subsequent performance. Further, given the cyclical nature of the theory, successful performance is a personal mastery experience and thus feeds back into further enhancing expectancies, which is predicted to further reduce self-focus and increase task-focus (external focus), thus creating a positive feedback loop.

Conversely, in what the authors call the vicious cycle, situations that reduce expectancies, thwart the need for autonomy, and cause an internal focus of attention are predicted to have a detrimental impact on performance and learning. Poor performance is expected to lower expectancies and increase the propensity to self-focus during performance, thereby inducing a negative feedback loop. Based on these hypothesized cycles, OPTIMAL theory includes the logical prediction that “conditions that optimize performance facilitate learning” (Wulf & Lewthwaite, 2016, pp. 1404; Prediction 12).

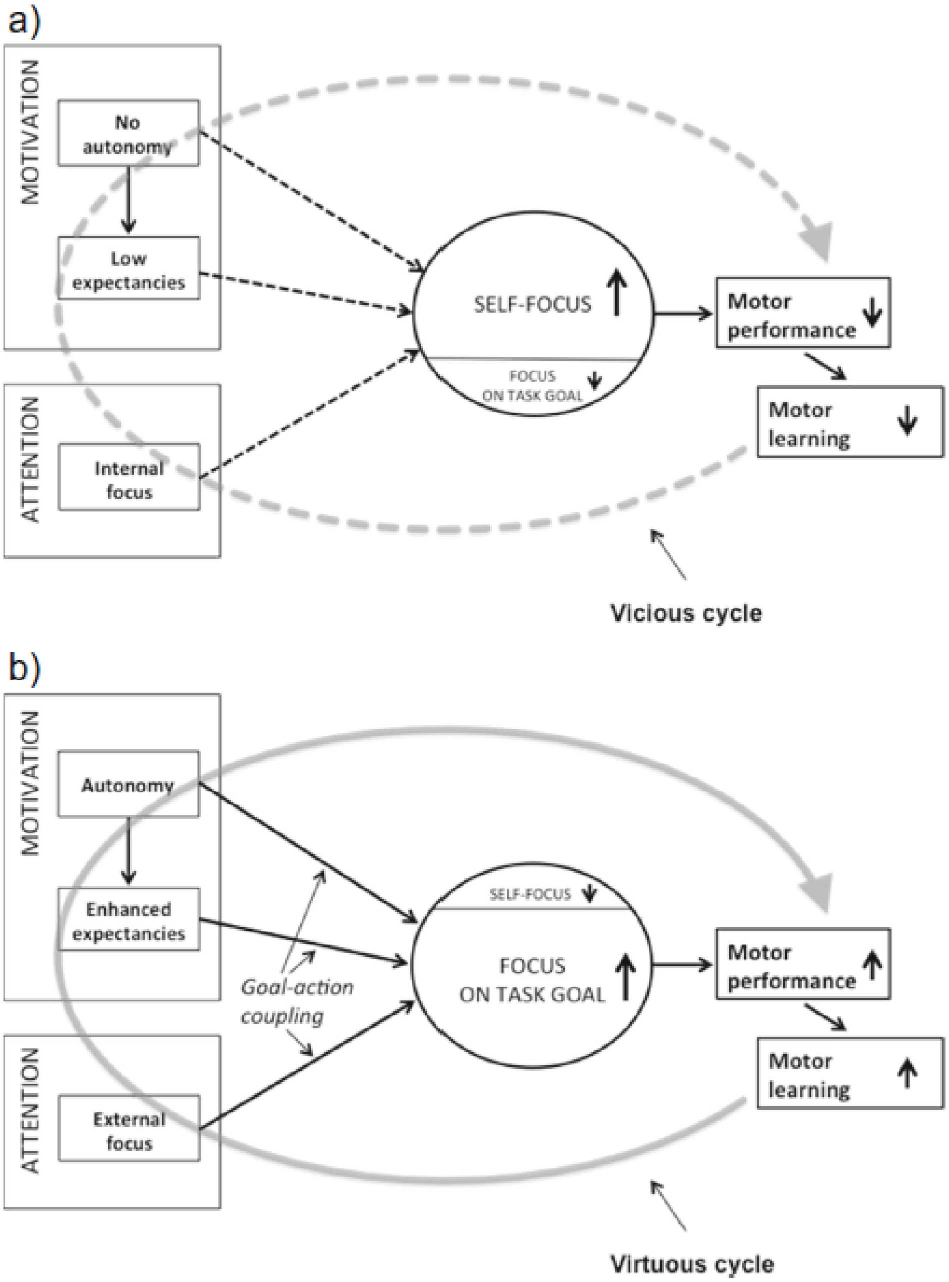

Figure 1.2. The vicious and virtuous cycles of OPTIMAL Theory.

1.4.5 Explicit predictions

Wulf and Lewthwaite (2016) include twelve explicit predictions that follow from their OPTIMAL Theory (Table 1.1).

Table 1.1

Predictions of the OPTIMAL Theory

1. When temporally associated with skill practice, conditions that enhance expectancies for positive outcomes trigger dopaminergic response and thereby benefit motor performance
2. Enhanced expectancies and autonomy support contribute to efficient goal-action coupling by readying the motor system for task execution
3. Autonomy support facilitates performance by enhancing expectancies
4. And external focus of attention directs attention to the task goal, enhancing goal-action coupling
5. And internal focus of attention impedes performance by directing attention to the self
6. Movement success resulting from an external focus enhances expectancies for future success
7. Enhanced expectancies and autonomy support facilitate motor learning by making dopamine available for memory consolidation and neural pathway development
8. Challenge, in the context of prevailing success, elicits a potentiating dopaminergic response that contributes to learning beyond success or challenge alone
9. Higher expectancies facilitate efficient switching from the default mode network to motor networks associated with the movement skill
10. An external attentional focus facilitates efficient switching from the default mode network to relevant motor networks
11. An internal attentional focus impedes efficient switching from the default mode network to motor networks associated with the movement skill

12. Generally, conditions that optimize performance facilitate learning.

Many of the twelve predictions make explicit the relationship between the three factors, their underlying mechanisms, and motor learning and performance. For example, Prediction 1 specifies that enhancing expectancies triggers a dopaminergic response that benefits performance. However, some predictions build on the underlying theories that buttress the mechanistic predictions in OPTIMAL Theory. For example, Prediction 8 follows from evidence that dopamine codes for reward prediction error, such that greater dopaminergic activity is present when rewards are greater than expected (Schultz, 2013). Success in the presence of prevailing challenge would result in a greater than anticipated reward, and therefore a greater dopaminergic response.

The specific OPTIMAL theory predictions tested in this dissertation are predictions 3, 7, and 12. Prediction 3 hypothesizes a) enhanced motor performance and b) enhanced expectancies when learners have their need for autonomy supported. Prediction 7 hypothesizes a) motor learning advantages with autonomy support and b) a dopaminergic response that drives the learning effects. While this dissertation addresses the impact of autonomy support on motor learning, the dopamine response to autonomy support is outside its scope. Prediction 12 states that, in general, conditions that enhance performance enhance learning.

1.5 Rationale for Experiments 1 and 2

Notably absent from OPTIMAL Theory are any predictions regarding feedback frequency or practice variability, the two variables best explained by the Guidance Hypothesis and Schema Theory, respectively. Given the rationale for positing the OPTIMAL Theory – that legacy theories fail to account for new findings – it is striking that OPTIMAL Theory does not appear to address findings the legacy theories appeared to explain. Instead, it seems that autonomy support is the purported solution to determining both variables in a practice environment, implying that differences in feedback frequency and practice variability are irrelevant if the learner is given choice over these variables. Otherwise, the presumed recommendation would be that the optimal schedule of feedback and practice variability be combined with the opportunity to make less consequential choices.

In the practical recommendations section of OPTIMAL theory, feedback and practice scheduling are in fact discussed within the context of choice being the only matter of consequence. Specifically, Wulf and Lewthwaite outlined two scenarios. In what they call the typical scenario, instructors select the tasks to be practiced, give corrective feedback, and describe how movements should be performed with respect to the coordination of body parts. Conversely, in what they call the OPTIMAL scenario, the instructor gives the learner choices, allows the learner to request feedback when they want it, mostly ignores mistakes, and gives instructions that induce an external focus of attention. In comparing the two scenarios, it appears that feedback and practice scheduling are largely to be chosen by the learner in the OPTIMAL scenario. Thus in stark contrast to the guidance hypothesis and schema theory, wherein certain schedules are predicted to be significantly less effective than others, the

OPTIMAL theory seems to suggest that any schedule a learner chooses is optimal because the act of choosing facilitates positive consequences for autonomy and expectancies.

The purpose of the first two experiments in this dissertation was to examine the independent and combined effects of autonomy support and feedback frequency (Experiment 1) and practice schedule (Experiment 2) on motor learning and performance. Autonomy support was manipulated by providing participants with instructionally-irrelevant choices, such as which colour golf ball to putt. In parallel, feedback and practice schedules were experimentally manipulated as part of factorial designs. Crossing autonomy support and scheduling variables allowed for the recommendations in OPTIMAL theory to be tested against the predictions of theories it was proposed to replace. OPTIMAL theory predicts that autonomy support will enhance acquisition performance as well as indices of learning and that, in general, conditions that enhance acquisition performance will facilitate learning. In contradiction to OPTIMAL theory, the guidance hypothesis and schema theory predict effects of feedback frequency and practice variability, independent of whether the learner's autonomy is supported. Further, Kantak and Winstein (2012) have argued that practice and feedback scheduling variables can have inconsistent effects on learning and performance, contrary to the OPTIMAL theory prediction. In order to be consistent with the theoretical perspectives tested in this dissertation, the absolute error analogue radial error was the criterion dependent measure in both experiments. The OPTIMAL theory makes central the linkage between the goals of an intended action and the specific actions required to accomplish those goals and absolute error measures the congruency of a given action outcome with the goal of the action. Similar arguments were made by Schmidt (1975) in schema theory where it was argued that absolute error should be the focal dependent measure when testing the theory.

1.6 Organization of the Dissertation

The remainder of the document will be organized as follows: Chapter 2 is in article format and describes Experiment 1. Chapter 3 will provide a general discussion of Experiment 1 and provide the rationale for methodological adjustments in Experiment 2. Chapter 4 is in article format and describes Experiment 2. Chapter 5 will describe a series of sensitivity analyses in order to assess the robustness of the primary findings in Experiment 2. Subsequently a general discussion of the results from Experiment 2 will be provided followed by an overview of the rationale for conducting the meta-analysis as the final study in the dissertation. Chapter 6 is in article format and describes the meta-analysis. Chapter 7 will provide an elaborated discussion of the meta-analysis results, present exploratory analyses, and situate the meta-analytic findings in the context of OPTIMAL theory. Chapter 8 will provide a general discussion of the main findings of this dissertation including their theoretical, practical, and meta-scientific implications.

2. Chapter 2

Article 1: Autonomy support and reduced feedback frequency have trivial effects on learning and performance of a golf putting task[2]

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[2] Submitted to *Human Movement Science*; reviews have been returned with an invitation to resubmit after making minor revisions. Some of those revisions have been made in this document.

2.1 Abstract

Optimizing Performance Through Intrinsic Motivation and Attention for Learning (OPTIMAL) Theory proposes that choices of any kind support an individual's need for autonomy, motivating them to learn and perform motor skills more effectively. Notably, the authors suggest asking learners to choose when to receive feedback in order to increase autonomy. Conversely, the Guidance Hypothesis predicts an impact of feedback schedule independent of motivational influences. The purpose of this experiment was to compare the relative and combined effects of autonomy and feedback schedule for the acquisition of a golf putting task without vision of results. Autonomy support (Autonomy support vs. yoked) and Knowledge of results (KR) schedule (100%-KR vs. 50%-faded-KR) were combined in a 2 X 2 factorial design. Participants (*N* = 56) in the Autonomy support groups were asked to choose from three colours of golf balls for each putt during 10 acquisition blocks. Yoked groups were yoked to the golf ball colour choices of their Autonomy support group counterparts. Participants in the 100%-feedback schedule groups were provided x- and y-coordinate KR following every putt during acquisition, while participants in the 50%-faded groups received KR after half of their putts, with feedback frequency decreasing over acquisition blocks. All participants completed a 24-hour delayed retention and transfer test without KR. The results were directionally consistent with OPTIMAL Theory yet the effects were not statistically significant and trivially small. The results were inconsistent with the Guidance Hypothesis.

Keywords: motor learning; motor performance; OPTIMAL Theory; Guidance Hypothesis; augmented feedback; autonomy

2.2 Introduction

Asking learners to make choices during practice, often called self-controlled learning, has been shown to enhance the retention of motor skills (for reviews see Sanli, Patterson, Bray, & Lee, 2013; Wulf, 2007; Wulf & Lewthwaite, 2016). A number of researchers have argued that robust benefits of choice may be caused by increases to intrinsic motivation (e.g., Sanli et al., 2013; Wulf & Lewthwaite, 2016). Although it has been known for some time that having the opportunity to choose is motivating (Deci & Ryan, 2000; Patall, Cooper, & Robinson, 2008), traditional theories of motor learning have minimized the direct influence of motivation on the retention of motor skills and placed more emphasis on informational contributions (e.g., Adams, 1971; Guadagnoli & Lee, 2004; Salmoni, Schmidt, & Walter, 1984; Schmidt, 1975). In line with these traditional theories, some researchers have attributed the benefits of choice primarily to spontaneous information processing differences that emerge under such learning conditions (Carter & Ste-Marie, 2017a; Chen & Singer, 1992; Chiviacowsky & Wulf, 2005). Wulf and Lewthwaite (2016) recently proposed the Optimizing Performance Through Intrinsic Motivation and Attention for Learning Theory (OPTIMAL Theory), and unlike the traditional theories, they proposed a central role for motivation in motor learning. According to OPTIMAL Theory, choice supports the basic psychological need for autonomy, which increases intrinsic motivation and directly enhances learning and performance.

Early demonstrations of self-controlled benefits arose from experimental designs in which instructionally-relevant choices were afforded to participants (Sanli, et al., 2013). When participants make instructionally-relevant choices, however, the impact of autonomy support is confounded with the modulation of relevant information by the learner. Therefore, it is perhaps impossible to isolate motivational and informational influences when learners make relevant choices. When learners make instructionally-irrelevant choices, any motor benefits would seem unlikely to be caused by informational mechanisms, leaving motivation as the more likely explanation. The first experiment to provide evidence that instructionally-irrelevant choices could enhance motor learning had participants practice a golf putting task with the goal of stopping shots in the centre of ten concentric circles (Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015). One group of participants were provided choice over which colour of golf ball they wanted to putt, whereas a second group were yoked to the choices made by the first group. Although the groups did not show differences during the acquisition phase, the choice group performed significantly more accurately on a 24-hour delayed retention test. In a follow-up experiment, Lewthwaite and colleagues asked learners to make two choices before beginning acquisition of a balance task: 1) which of two tasks to complete following the retention test the next day, and 2) which of two paintings to hang on the wall of the laboratory. Consistent with the results of the first experiment, the choice group performed significantly better on a delayed retention test than their yoked counterparts. Lewthwaite and colleagues interpreted their findings as direct evidence that autonomy support benefits motor learning. Notable, however, is that others have failed to replicate the results of this experiment with the use of a similar protocol with a different task (Carter & Ste-Marie, 2017b; Grand, Daou, Lohse, & Miller, 2017).

Wulf, Lewthwaite, and their colleagues have reported learning and performance benefits from instructionally-irrelevant choices in five subsequent experiments. For example, asking participants to choose the colour of balls to throw (Wulf, Chiviacowsky, & Cardozo, 2014), the style of bowling ball to bowl (Abdollahipour, Nieto, Psotta, & Wulf, 2017), the symbol to have on the floor where a countermovement jump will be performed (Chua, Wulf, & Lewthwaite, 2018), and the colour of the mat underneath a cone to be lassoed (Wulf, Itwatsuki, Machin, Kellogg, Copeland, & Lewthwaite, 2017), have all been more effective than yoking participants to these choices. From the perspective of OPTIMAL Theory, Wulf and Lewthwaite hypothesize that autonomy support is the primary mechanism underlying the benefits observed in all self-control experiments, regardless of the instructional relevance of the choices.

As a consequence of these, and other, findings, a recommendation presented by Wulf and Lewthwaite (2016) is for coaches, therapists, physical educators, and other applied instructors to provide the learners with choice over their feedback schedule; a recommendation which joins a chorus of calls by others (Aiken, Fairbrother, & Post, 2012; Andrieux, Danna, & Thon, 2012; Chen et al., 2002; Chiviacowsky, Wulf, de Medeiros, Kaefer, & Tani, 2008; Chiviacowsky, Wulf, Lewthwaite, & Campos, 2012; Fairbrother, Laughlin, & Ngyuyen, 2012; Hemayattalab, Arabameri, Pourazar, Ardakani, & Kashefi 2013; Janelle, Kim, & Singer, 1995; Patterson & Carter, 2010; Sanli & Patterson, 2013; Sanli et al., 2013; Sheaves, Snodgrass, & Rivett, 2012). This recommendation is in sharp contrast to that which would be derived from traditional motor learning theories. Numerous researchers have found that different feedback schedules have varying impacts on motor learning and performance (e.g., Lee & Carnahan, 1990; Salmoni et al., 1984; Schmidt, Young, Swinnen, & Shapiro, 1989; Winstein & Schmidt, 1990). Most results have been interpreted within the Guidance Hypothesis framework in which high frequencies of feedback can become a crutch for learners, enhancing acquisition performance but degrading retention performance relative to a reduced feedback schedule (Salmoni et al., 1984). Wulf and Lewthwaite (2016), however, did not speak overtly to these findings and we argue that it may be premature to recommend that learners be provided choice over feedback scheduling because no research as of yet has unconfounded the effect of the feedback schedules chosen by participants with the effect of choice.

Given the findings of instructionally-irrelevant choice, however, it is possible to combine autonomy with a feedback schedule manipulation in a factorial design. Isolating the effects of feedback schedule and choice will allow us to speak more directly as to whether the above recommendation is warranted. In the present experiment we crossed autonomy support and feedback schedule; participants were assigned to one of four groups: Autonomy and 100%-KR, Autonomy and 50%-faded-KR, Yoked and 100%-KR, and Yoked and 50%-faded-KR. The groups completed a pre-test followed by ten acquisition blocks of a novel motor task – putting golf balls from behind a screen to a target on an indoor putting green. Retention and transfer tests were conducted the day after acquisition. Augmented KR was provided verbally to the learners in the form of horizontal and vertical units of error. Participants in the 100%-KR groups received KR after every putt during acquisition. The 50%-faded-KR groups received an average of 50% feedback, with more feedback during early blocks and less feedback on later blocks. Participants in the autonomy support groups were asked to choose from three colours of golf ball to putt on each trial while their counterparts in the yoked groups followed the same colour sequence without choice.

We tested hypotheses from OPTIMAL Theory and the Guidance Hypothesis. The primary hypotheses of interested pertained to physical putting performance. OPTIMAL Theory predicts:

a) superior learning and performance when participants receive autonomy support, reflected by a main effect for Autonomy support on the final acquisition block, retention, and transfer, b) variables that benefit acquisition performance will also benefit retention performance, reflected by a lack of Block (final block of acquisition, retention, transfer) X Factor interactions, c) the benefit of autonomy support does not depend on the feedback schedule, reflected by either no main effect of KR schedule or an Autonomy support X KR schedule attenuation interaction, wherein KR schedule has a null effect when learners have autonomy. In contrast, the Guidance Hypothesis predicts more effective acquisition performance but less effective post-test performance for groups receiving 100%-KR, reflected by a KR schedule X Block (final block of acquisition, retention, transfer) reversal interaction. This prediction is incompatible with predictions b) and c) from OPTIMAL Theory, therefore the results of this experiment can support only one of the two sets of hypotheses.

Of secondary interest were hypotheses related to the impact of choice on perceived autonomy and self-efficacy. OPTIMAL Theory predicts making choices increases perceptions of autonomy, which would be reflected in a main effect of Autonomy support when analyzing the Basic Psychological Needs in Sport questionnaire data. Further, it is predicted that autonomy support enhances perceptions of self-efficacy, reflected by a main effect for Autonomy support when analyzing the self-efficacy questionnaire data.

2.3 Method

2.3.2 Participants

Data were collected from 56 participants (40 males, 16 females) who were recruited to participate in this experiment. Participants were from the Ottawa region with an average age of 24.1 years (*SD* = 11.4). The inclusion criteria in this experiment required that participants had no more than 10 golf-putting experiences in the past year (*M* = 1.9, *SD* = 2.75). Participants were randomly assigned to one of four experimental groups with two constraints: Groups were balanced for gender and the first two participants were assigned to the choice groups to allow for random assignment and yoking thereafter. All participants provided written informed consent in accordance with the policies of the University's Research Ethics Board.

2.3.2 Task and materials

The experimental task was to putt golf balls of three different colours on an indoor putting green to a target 1.83m away during pre-test, acquisition, and retention blocks, and 2.13m away during a transfer block. Similar left- or right-handed blade putters were provided to participants for use in the experiment. The goal was to attempt to stop the golf ball directly over the target while having vision of the putt occluded by a 2m tall by 1m wide curtain positioned 60cm in front of the participant. The curtain was suspended 15cm above the putting green to allow the balls to roll underneath. The surface of the putting green had a 5cm X 5cm grid imprinted on its surface to assist in measurement, as well as in the provision of feedback.

Four questionnaires were used at different time-points in the experiment. First, questions concerning the participant's age, sex, the frequency of their putting experiences in the past year and in the past five years, and their previous experience in sports requiring use of an implement was created to gather demographic information (demographic questionnaire). Second, the Basic Need Satisfaction in Sport Scale (BNSSS; Ng, Lonsdale, & Hodge, 2011) was used to obtain a measure of autonomy. For the BNSS, participants rate the veracity of ten statements using a 7-point Likert-type scale, with “not true at all” and “very true” anchoring 1 and 7 respectively. Items probe autonomy need satisfaction, for example: “In this study, I get to make choices,” “In this study, I get opportunities to make decisions,” and “In this study, I feel I am doing what I want to be doing.” Third, participant’s perception of self-efficacy for the golf-putting task was assessed (self-efficacy questionnaire). A mat with three concentric squares of differing colours was placed directly above the target to illustrate different amounts of error. Participants would indicate how many of their subsequent ten putts they believed they would stop in each of the three zones, with each zone denoting increasing levels of accuracy. Finally, the fourth questionnaire was a one-item test that served to index participants’ perceptions of the level of relevance of the colour of the ball on putting performance (relevance questionnaire). Participants would rate their agreement to the statement: “The colour of the golf ball had an effect on my performance of the golf putting task.” using a 7-point Likert-type scale, wherein 1 was anchored with strongly agree, 4 with neither agree nor disagree, and 7 with strongly disagree.

2.3.3 Procedure

All participants completed a three-phase experiment which involved a pre-test, acquisition, and post-test phases. Prior to completing the pre-test, it was explained to each participant that the goal of the putting task was to stop each putt on a white dot 1.83m from their starting position. Participants were shown the location of the target before going behind the occlusion screen to prepare to putt. Each participant was instructed to place each golf ball inside a white circle indicating the starting position. Golf balls were taken from a rack in a pre-specified colour order that was counterbalanced for the pre-test. Participants completed 10 putts without feedback as a pre-test of their putting accuracy. The X and Y coordinates of each putt were measured by hand with the assistance of a 5cm X 5cm grid. Hancock, Butler, and Fischman (1995) recommend collecting 2-dimensional error scores to allow for potential analyses of bias and consistency in addition to absolute error. Following the putts, each participant then completed the demographics questionnaire, followed by the self-efficacy questionnaire and BNSSS to serve as baseline measures.

After completing the pre-test phase, participants transitioned into the acquisition phase. First, participants were explained how feedback would be provided using the 5cm grid system imprinted on the putting green. Each participant's comprehension of the feedback was tested by placing a golf ball in a square that was two units long and two units to the left and asking them to provide the feedback that would be given. Infrequently, participants would need to be retested on a location 3 units to the right and one unit short if they had provided incorrect feedback on their first test.

Participants then completed ten blocks of five putts while experiencing one level of each independent variable, resulting in four different groups: (1) Choice with 50%-faded-KR, (2) Choice with 100%-KR, (3) No choice with 50%-faded-KR, and (4) No choice with 100%-KR. Augmented feedback was provided in the form of grid units of error on the X and Y axis and the frequency depended on the experimental condition: Participants in the 100%-KR groups received KR following each putt, while participants in the 50%-faded-KR groups received KR following an average of 50% of their putts, with a greater volume of KR provided early in acquisition. The KR schedule in the 50%-faded condition was 80% on Block 1, 60% on Blocks 2-5, 40% on Blocks 6-9, and 20% on Block 10 (see Winstein & Schmidt, 1990, Exp. 2 for a similar scheduling procedure). The KR-delay interval was tested during piloting of the experiment and was consistently between 8s and 15s. The inter-trial interval was self-paced as participants selected their next ball from the tray, placed it in the starting position, and executed the putt. Participants in the Autonomy support groups were asked to choose any colour of golf ball they preferred out of a tray holding 5 balls of each colour (orange, green, and yellow) in the same colour order as their counterbalanced pre-test. Participants in the Yoked groups were asked to putt golf balls of the same colour as those chosen by a counterpart in the Autonomy support group. This was accomplished by placing five balls for each block in the determined colour order in the tray and asking participants to select balls from left to right. Participants in the Yoked-50%-faded-KR group were each yoked to the colour choices of a counterpart in the Autonomy support-50%-faded-KR group, and likewise for the participants in the 100%-KR groups. Immediately after completing the putts, participants returned to the laptop computer that was available and completed the self-efficacy questionnaire and BNSSS measures. In addition, they answered the single-item relevance questionnaire.

After an approximate 24-hour delay, the post-test phase began. During this phase, participants returned and first completed the self-efficacy questionnaire. They were then instructed that they were to try to putt to the same target as the day prior, but would no longer receive KR on their performance. Participants completed 10-trials in this no-KR retention test, followed by a 10-trial no-KR transfer test to a target 50cm farther than previously practiced. Prior to the transfer test, participants were shown the new target and asked to complete another self-efficacy questionnaire pertaining to their next 10 putts.

2.3.4 Data analysis

Performance and learning hypotheses from OPTIMAL Theory and the Guidance Hypothesis were tested by submitting mean putting radial error data to a 2 (Autonomy support) X 2 (KR schedule) X 3 (Block: 10th, retention, transfer) analysis of covariance (ANCOVA) with repeated measures on the final factor and the pre-test scores included as a covariate.

For the variables of secondary interest, the OPTIMAL Theory prediction that being provided choice enhances autonomy need satisfaction was tested by submitting the mean end-of-acquisition BNSSS data to a 2 (Autonomy support) X 2 (KR schedule) ANCOVA with baseline mean BNSSS included as a covariate. Further, a 2 (Autonomy support) X 2 (KR schedule) X 3 (Time point: end of acquisition, pre-retention, pre-transfer) mixed ANCOVA with repeated measures on the final factor and baseline self-efficacy included as a covariate was conducted to test the OPTIMAL Theory prediction that Autonomy support enhances self-efficacy. Consistent with recommendations by Schneider, Avivi-Reich, and Mozuraitis (2015), we first centered all covariates before including them in any analyses with a within subjects factor.

2.4 Results

2.4.1 Descriptive statistics. The descriptive statistics for each group and measure can be seen in Table 1. Of note, the 100%-KR groups putted with substantially greater radial error than the

50%-faded-KR groups on the pre-test[3]. Conversely, the Autonomy support and Yoked groups exhibited similar radial error on the pre-test. In general, putting radial error decreased for all groups from pre-test to block 10, and then increased on the delayed 24-hour retention test and again on the transfer test. Indicative of motor learning, overall putting performance was significantly more accurate on the 24-hour delayed retention test than on the pre-test *F*(1, 55) = 14.36, *p* < .001.

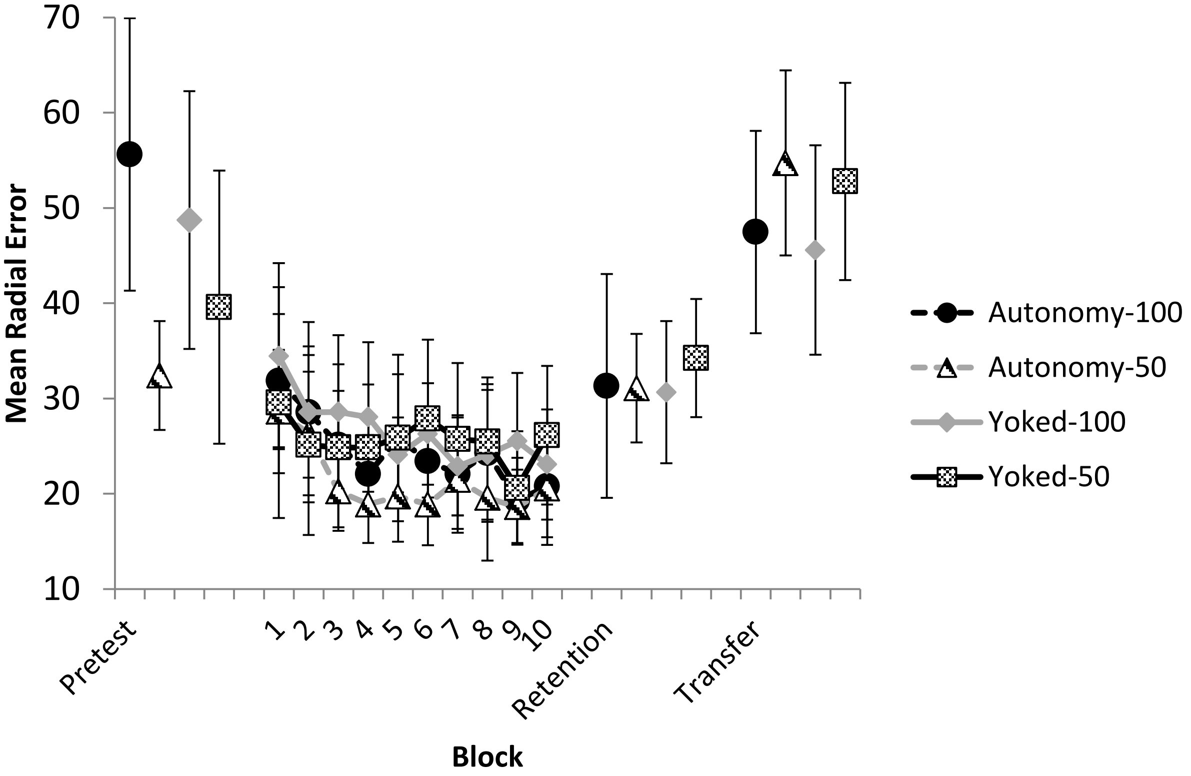

Figure 2.1. Putting mean radial error on pretest, acquisition, retention and transfer blocks. Error bars represent 95% confidence intervals.

Table 2.1

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[3] Pre-test data were not submitted to inferential statistics because any differences noted would be the result of chance, rendering the test illogical (Mutz, Pemantle, & Pham, 2019).

Mean (SD) radial error (cm) for each group at pre-test, 10th block of acquisition, retention and transfer.

Group	Pre-test	10th Block	Retention	Transfer
100%-KR/ Choice	55.63(24.77)	20.79(10.67)	31.31(20.34)	47.49(18.4)
100%-KR/ Yoked	48.74 (23.44)	23.08(10.00)	30.66(12.92)	45.59(19.05)
50%-KR/ Choice	32.43(9.89)	20.56(8.88)	31.08(9.85)	54.73(16.83)
50%-KR/ Yoked	39.59(24.84)	26.15(12.59)	34.25(10.75)	52.80(17.92)

2.4.2 Performance and learning. Hypothesis tests were conducted while adjusting for centered pre-test putting performance, which was significantly related to performance across test blocks, *F*(1, 51) = 5.807, *p* = .02. The 100%-KR groups putted more accurately than the 50%-faded-KR groups on the 10th acquisition block, retention, and transfer tests (see Table 1). The main effect of KR was statistically significant, *F*(3, 51) = 4.071, *p* = .049 (see Figure 1). The Autonomy support groups putted more accurately than the Yoked groups on the 10th acquisition block and retention test, but less accurately on the transfer test, however, these differences were not statistically significant, *F*(3, 51) = .147, *p* = .703 (see Figure 2). The KR schedule X Autonomy support interaction also failed to reach statistical significance, *F*(3, 51) = .087, *p* = .987.

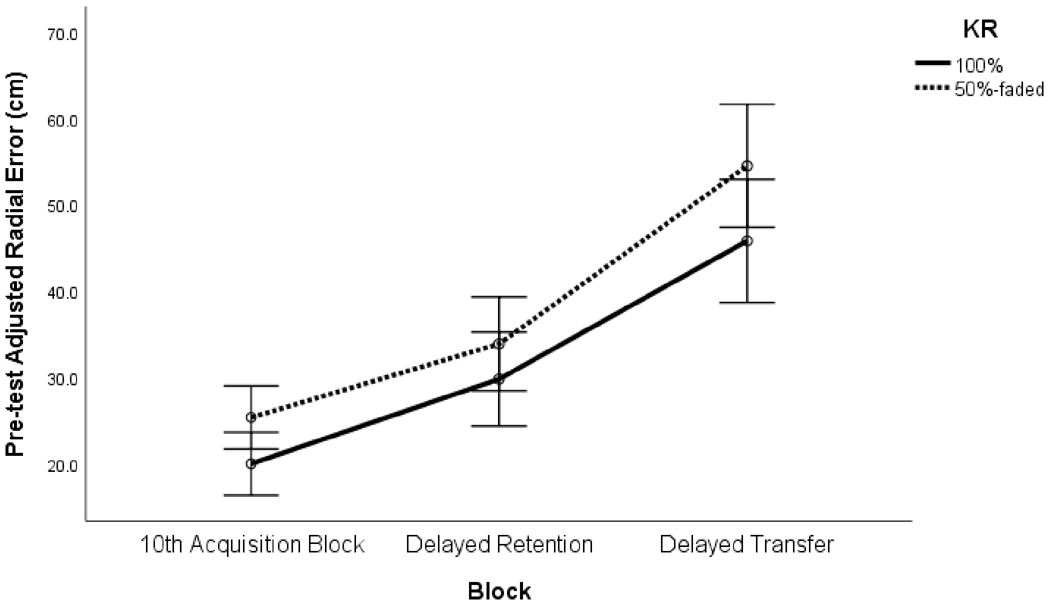

Figure 2.2. Mean radial error as a function of block and Feedback condition. Error bars represent 95% confidence intervals.

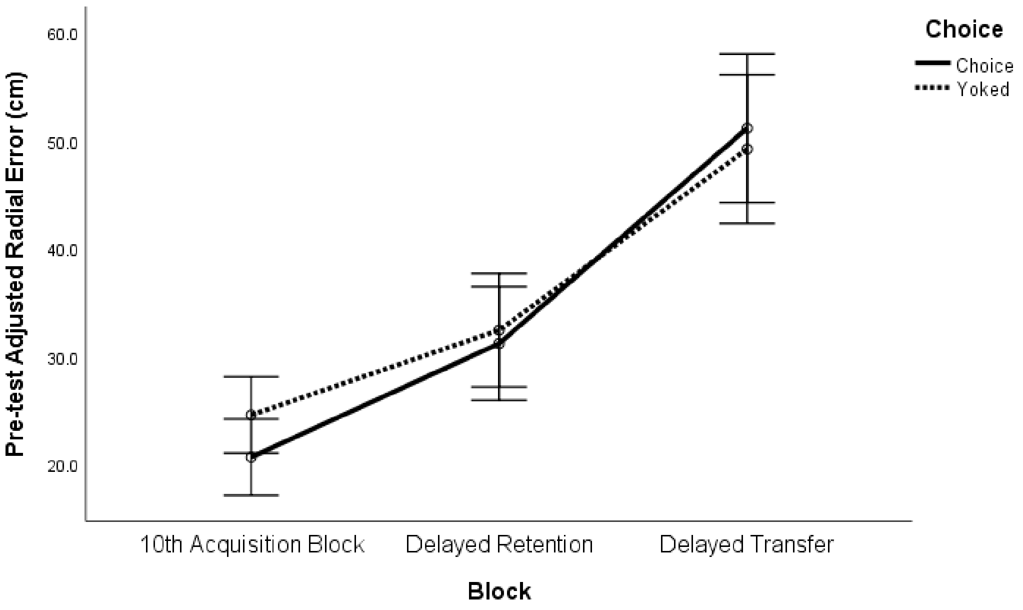

Figure 2.3. Mean radial error as a function of block and Choice condition. Error bars represent 95% confidence intervals.

2.4.3 Choice and autonomy. Baseline BNSSS score was a statistically significant predictor of end-of-acquisition BNSS score, $F(1, 51) = 54.39$, $p < .001$. The Autonomy support groups had higher BNSSS scores at the end of acquisition ($M = 5.40$, $SD = .740$) than the Yoked groups ($M = 4.65$, $SD = 1.16$), yet, after adjusting for baseline BNSSS, the main effect of Autonomy support just failed to reach statistical significance, $F(3, 51) = 3.66$, $p = .061$.

2.4.4 Autonomy support and self-efficacy. Centered baseline self-efficacy was significantly related to self-efficacy across time points, $F(1, 51) = 97.90$, $p < .001$. The Autonomy support groups had higher self-efficacy scores at end-of-acquisition, pre-retention, and pre-transfer time points (see Table 2). After adjusting for baseline self-efficacy, however, the main effect of Autonomy support failed to reach statistical significance, $F(3, 51) = 2.71$, $p = .108$.

Table 2.2

Mean (SD) self-efficacy at pre-test, end of acquisition, retention, and transfer.

Group	Pre-test	End of Acquisition	Retention	Transfer
100%-KR/ Choice	2.95(1.15)	3.24(1.60)	2.95(1.60)	2.26(0.76)
100%-KR/ Yoked	3.07 (1.07)	2.93(1.14)	2.62(1.10)	2.36(1.22)
50%-KR/ Choice	2.76(0.95)	3.29(1.44)	2.71(1.01)	1.95(1.13)
50%-KR/ Yoked	2.73(1.18)	2.63(1.33)	2.31(1.22)	1.71(0.90)

Note: Pre-test and end of acquisition self-efficacy measures were administered following putting performance; retention and transfer self-efficacy were administered prior to putting performance.

2.4.5 Interim discussion. The present experiment was designed to test five predictions from OPTIMAL Theory. The results were directionally consistent with four of the predictions but failed to reach statistical significance for each prediction. The OPTIMAL Theory prediction that KR schedule would not have a main effect or that there would be a KR schedule X Autonomy support interaction was not supported. Instead, there was a significant main effect for KR schedule and the KR schedule X Autonomy support interaction did not occur.

The present experiment was also designed to test the Guidance Hypothesis. Although the 100%-KR group performed more accurately on the final block of acquisition, the predicted reversal interaction did not occur and the 100%-KR groups continued to perform more accurately than the 50%-faded-KR groups on the retention and transfer tests. The Guidance Hypothesis was not supported by the present experiment.

The main effect for KR schedule on putting accuracy was not predicted by either theoretical perspective tested in this experiment and was only marginally statistically significant. Given the large difference in pre-test radial error between levels of KR schedule, additional data were collected for the purpose of testing the robustness of this main effect. Specifically, 16 additional male participants were recruited to participate in this experiment and were assigned to their groups using biased-coin randomization (Frane, 1998). Biased–coin randomization is used to balance groups probabilistically on a prognostic covariate, in this case pre-test absolute error. After collecting pre-test absolute error, four ANOVAs were conducted with the prospective participant added to each group. Participants were then assigned to a group with probabilities equal to $p_1/(p_1 + p_2 + p_3 + p_4)$, and so on, with a constraint that the groups must remain balanced.

2.4.6 Test of robustness. After collecting 16 additional participants assigned to experimental groups via biased-coin randomization, all analyses previously described were conducted again. The main effect for KR schedule on putting accuracy was no longer statistically significant, $F(3, 67) = 1.263$, $p = .265$. The statistical significance of all other planned analyses did not change with the inclusion of 16 additional participants; for example, the main effect of autonomy support on putting accuracy, *F*(3,67) = .062, *p* = .804, the main effect of autonomy support on perceived autonomy support, *F*(1, 67) = 2.886, *p* = .094, and the main effect of autonomy support on self-efficacy, *F*(2,67) = 1.344, *p* = .251 also did not meet significance levels.

2.5 Discussion

The purpose of the present experiment was to assess the recommendation in OPTIMAL Theory that learners be provided choice over their own feedback schedules (Wulf & Lewthwaite, 2016, p. 1406). Although there is substantial evidence that asking learners to make choices during practice is more effective than yoking learners to the choices of others, we argue that this recommendation was premature because it appears to ignore other augmented feedback findings within the motor learning literature. More specifically, previous experiments have reported systematic effects of varying feedback frequency and schedule on subsequent motor learning outcomes (e.g., Winstein & Schmidt, 1990; Wulf & Schmidt, 1989. A problem with applying self-controlled feedback learning experiments to applied settings is that choice and augmented feedback have been confounded within the design. According to OPTIMAL Theory, instructionally-relevant choices, like choosing a feedback schedule, enhance learning and performance via the same mechanism as instructionally-irrelevant choices, like choosing golf ball colour (Lewthwaite et al., 2015; Wulf & Lewthwaite, 2016). Therefore, in the present experiment we were able to cross the effect of autonomy with feedback schedule in a factorial design by providing choice (or not) of golf ball colour and manipulating feedback schedule experimentally. This allowed us to isolate the independent effects of each variable while also exploring a potential interaction between them, which, in turn, tested competing predictions that arose from OPTIMAL Theory (Wulf & Lewthwaite) and the Guidance Hypothesis (Salmoni et al., 1984).

In particular, OPTIMAL Theory predicts a main effect for Autonomy support that is independent of KR schedule, while the Guidance Hypothesis predicts a main effect for KR schedule that is independent of Autonomy support. In this regard, OPTIMAL Theory's prediction was supported directionally, but was not statistically significant. Conversely, the prediction from the Guidance Hypothesis was not supported directionally; instead the 100% group had greater performance and learning gains than the 50% group. These differences, however, were not significant, and thus the null hypothesis could not be rejected. Further, OPTIMAL Theory predicts that the effects of practice variables, which should include KR, would be directionally consistent during acquisition and retention, while the Guidance Hypothesis predicts a reversal interaction such that higher amounts of KR would lead to better acquisition but poorer retention/transfer. The data here aligned with OPTIMAL Theory; no significant interaction was obtained for performance across the last block of acquisition and the retention and transfer tests. Finally, OPTIMAL Theory implies that autonomy support would attenuate any feedback frequency effects when it is present, such that autonomy support and feedback schedule would not combine additively. This was also somewhat supported as there was no main effect for feedback schedule to be attenuated.

Although the present experiment failed to find adequate evidence to reject the null hypothesis for any comparison of interest, the pattern of results are mostly consistent with the predictions of OPTIMAL Theory. Participants in the Autonomy support groups demonstrated more accurate putting performance overall during the end of acquisition and post-test blocks. Further, KR frequency did not appear to modulate the effect of Autonomy support. Performance differences during acquisition and post-testing were directionally consistent, rather than exhibiting the reversal interaction predicted by the Guidance Hypothesis. Measures of autonomy support and self-efficacy revealed slightly higher scores for participants in the Autonomy support groups than their Yoked counterparts. Despite these directionally consistent outcomes, we contend that caution is still needed before recommending that learners' self-control their feedback schedule in applied settings.

An important point to consider is that the effect of Autonomy support observed in the present experiment was substantially smaller than in the extant literature (McKay, Carter, & Ste-Marie, 2014). For example, a meta-analysis (McKay et al., 2014) of published and unpublished self-controlled learning experiments reported that a random effects model of 23 experiments resulted in an estimated effect size of $g = .61$. The present experiment estimated the effect size of autonomy support as $g = 0.1$ with a 90% confidence interval of -0.33 - .53. A two-one-sided-tests analysis (Lakens, 2017; Simonsohn, 2016) comparing the effect observed in this experiment to the meta-analytic estimate was conducted and revealed the effect in this experiment was significantly smaller than the meta-analytic estimate, $t(70) = 2.06$, $p = .0216$. McKay and colleagues' (2014) meta-analysis, however, failed to account for publication bias, *p*-hacking, or other selection effects that have been demonstrated to bias effect size estimates in meta-analyses (Simonsohn, Nelson, & Simmons, 2014; Simonsohn, Simmons, & Nelson, 2015). The present results suggest the true effect of autonomy on motor learning may be substantially smaller than previously reported and more rigorous meta-analytical techniques on the data are warranted.

Although researchers have debated the robustness of the Guidance Hypothesis (see: Magill & Anderson, 2012; Wulf & Shea, 2004), it still remains a dominant paradigm for explaining and prescribing augmented feedback scheduling (Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2018). The present experiment failed to find results that were directionally consistent with its prediction. The 100%-KR groups putted more accurately than the 50%-faded-KR groups during acquisition and post-testing, showing no evidence of an overreliance on augmented feedback during no-KR retention and transfer testing. Magill and Anderson (2012) have argued that high frequency KR schedules may not lead to a dependency if the intrinsic task-related feedback is more salient and useful than the augmented feedback. We doubt this was the case in the present experiment as a large and statistically significant improvement in putting accuracy from the no-KR pre-test to the first block of acquisition was observed, $F(1,52) = 40.98$, $p < .001$. If the predicted guidance effect was absent due to more salient intrinsic feedback, we would not expect the initiation of augmented feedback to have such a large impact on putting accuracy.

The OPTIMAL Theory recommendation to allow learners to schedule their own augmented feedback is at odds with the Guidance Hypothesis, which predicts different learning effects for different feedback schedules. The present experiment did not find evidence to support the Guidance predictions and did observe a pattern of results consistent with OPTIMAL Theory; although all effects observed were small and call into question the practical significance of autonomy support for motor learning and performance. Future work is needed to clarify the boundaries of which effects are meaningful to motor learning researchers and practitioners and which are not. Motor learning researchers should perhaps work to define a smallest effect size of interest (SESOI; Lakens, 2014; 2017). Then, rather than simply failing to reject the null hypothesis, researchers can test small effects against the SESOI in an equivalence test, allowing for conclusions about an independent variable's (in)effectiveness.

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3. Chapter 3

Elaborated Discussion of Article 1

A motivating question for the dissertation is whether providing choice increases autonomy, self-efficacy, motor performance and motor learning, and if this effect is sufficient to optimize learning and performance even if the choices provided result in suboptimal feedback or practice schedules. Wulf and Lewthwaite (2016) recommend providing choice over feedback and practice schedule in order to enhance autonomy, yet motor learning researchers have hypothesized an important role for feedback and practice schedules for decades (e.g.,Salmoni, Walter, & Schmidt., 1984; Schmidt, 1975). It is unclear whether Wulf and Lewthwaite recommend learners choose their feedback and practice schedules because such choices are convenient or because a number of experiments have demonstrated benefits for self-scheduling relative to a yoked-schedule. While it may be convenient to ask learners to choose their own feedback schedule, the current lack of evidence supporting a beneficial effect of learner- versus instructor-scheduling suggests caution in adopting a self-controlled feedback strategy. Previous experiments that have found benefits to self-scheduling relative to a yoked schedule do not test the efficacy of self-scheduling in practice, since the alternative to a self-selected schedule is an instructor selected schedule not a yoked schedule. The lack of research comparing self-scheduling to instructor-scheduling reflects the difficulty in comparing one instructor’s schedule choices to another. For example, it seems plausible that a self-controlled feedback schedule could be more effective than feedback determined by a novice coach but less effective than an experienced coach, but this line of research has not been developed. Another approach to this question is to consider whether the specific schedule has an impact on learning and performance and whether that effect changes if the learner has the opportunity to make choices. Although choosing when to receive feedback may engage processes not captured by an instructionally-irrelevant choice, OPTIMAL theory specifies autonomy support as the mechanism for choice effects and stipulates these effects are caused by any type of choice. Therefore conducting an experiment that manipulates instructionally-irrelevant choice and feedback schedule independently allows for a test of the OPTIMAL theory predictions and recommendations that is presently missing in the literature.

In Experiment 1, the OPTMIAL theory predictions that providing choice enhances autonomy, self-efficacy, motor performance, and motor learning were tested, as was the implication that when learners are motivated by choice, the feedback schedules they receive will be irrelevant. Further, the guidance hypothesis, which predicts that receiving knowledge of results (KR) after every practice trial is beneficial to practice performance but detrimental to learning, was tested against the OPTIMAL theory predictions. The guidance hypothesis is inconsistent with OPTIMAL theory in two ways: First, OPTIMAL theory suggests learners scheduling their own KR is optimal, while the guidance hypothesis predicts systematic effects to different feedback schedules. Second, OPTIMAL theory predicts that variables that enhance practice performance will also benefit learning, while the guidance hypothesis predicts a ‘reversal effect,’ wherein high frequencies of feedback are more effective during practice but less effective for learning.

Contrary to both OPTIMAL theory and guidance hypothesis predictions, there were no significant effects of autonomy support or feedback schedule in Experiment 1. The results were directionally inconsistent with guidance hypothesis: The 100%-KR groups performed more accurately during practice and post-testing rather than experiencing the predicted ‘reversal effect.' Although the results were directionally consistent with OPTIMAL theory predictions, the observed effects of autonomy support on motor learning and performance were trivially small. The failure to observe statistically significant benefits to autonomy support comes despite collecting an initial sample 60% larger than the average self-controlled learning experiment, including a prognostic covariate in the analysis, and including the same motor skill used in the original experiment demonstrating a benefit to instructionally-irrelevant choice (Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015).

3.1 Limitations

There were three primary limitations in Experiment 1. First, there was substantial baseline imbalance on the pre-test radial error between the two levels of KR schedule. This baseline imbalance was larger in the initial sample of 56 participants than the final sample (*N* = 72) because the biased coin randomization technique was applied when collecting the 16 additional participants (Frane, 1998). Nevertheless, there was substantial baseline imbalance in the final sample as well. Baseline imbalance adds error to the model but is mitigated by inclusion as a covariate. Simulating 200 experiments with varying degrees of baseline imbalance, Senn (2019) demonstrated that ANCOVA provides 95% long run coverage of the true effect even with large baseline imbalance. Second, the retention test and transfer test were not counterbalanced therefore differences between the tests cannot be separated from order effects. Differences between the tests were not part of the *a priori* research questions but not counterbalancing prevents *post hoc* exploratory analyses. Third, recruiting participants directly through word of mouth is a precarious sampling technique with only two researchers engaged in recruitment efforts. It is possible the social networks of the researchers were comprised of some subset of the population who respond differently to the independent variables than the general population.

3.2 Moving forward

The status of the OPTIMAL theory predictions and recommendations following Experiment 1 remain uncertain. Feedback schedule did not produce robust effects and therefore may be a viable variable for self-scheduling. However, choice did not significantly enhance perceived autonomy, self-efficacy, motor performance, or motor learning, calling into question the relevance of providing small choices during practice. Therefore, in Experiment 2, sample size was increased in order to conduct the most powerful experiment on self-controlled learning yet. Further, we switched to a dart-throwing task completed with the non-dominant hand in case the failure to observe meaningful effects in Experiment 1 was somehow due to the nature of the putting task. Autonomy was crossed with practice schedule, another variable recommended by Wulf and Lewthwaite for learners to control. Conversely, schema theory (Schmidt, 1975) predicts that practice schedule will have systematic effects on motor learning. Further, as with feedback schedule, it has been suggested that practice schedule can lead to 'reversal effects' (Kantak & Winstein, 2012), which is inconsistent with OPTIMAL theory.

The purpose of Experiment 2 is to perform a high-powered test of the predicted effects of autonomy support on self-efficacy, motor performance, and motor learning. In doing so, Experiment 2 is designed to answer questions that emerged from the null results observed in Experiment 1: Does the effect of autonomy support replicate in a pre-registered experiment?

Will the effect of practice schedule replicate? Are the recommendations provided by Wulf and Lewthwaite (2016) to allow learners to choose their practice schedule warranted?

4. Chapter 4

Article 2: Autonomy support via instructionally-irrelevant choice not beneficial for motor performance[4]

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[4] Submitted to *Research Quarterly in Exercise Science*; reviews have been returned with an invitation to resubmit with major revisions. Some of these revisions have been made in this document.

4.1 Abstract

4.1.1 Purpose: The Optimizing Performance Through Motivation and Attention for Learning (OPTIMAL) theory predicts that providing learners with choices during skill acquisition will enhance their acquisition performance, motor learning, and expectancies (Wulf & Lewthwaite, 2016). Based on this theory, it is recommended that instructors ask learners to choose which tasks to practice in applied settings. This experiment tested these predictions by crossing autonomy support with practice schedule in a 2 X 2 factorial design.

4.1.2 Method: Participants (*N* = 128) practiced a novel non-dominant hand dart throwing task either with choice over the colour of the dart flights (autonomy) or yoked to a counterpart's choices (yoked). Further, participants either practiced throwing darts to three different targets in equal amounts (variable) or throwing to the same target for all practice trials (constant). All participants completed a 9-trial pre-test, baseline autonomy and self-efficacy measures, and a subsequent acquisition phase of 36 dart-throws. Participants completed autonomy and self-efficacy measures immediately following acquisition and returned to complete 24-hour delayed retention and transfer tests. Data were analyzed according to a pre-registered analysis plan that included pre-test and gender as covariates.

4.1.3 Results: The autonomy groups reported significantly greater perceived autonomy at the end of acquisition. There were no significant effects on a delayed transfer test. The autonomy groups performed with significantly greater error across acquisition and transfer. Practice schedule produced an attenuation interaction with the constant groups performing more accurately during acquisition but less accurately during transfer than the variable groups.

4.1.4 Conclusions: These results are inconsistent with OPTIMAL theory.

Keywords: OPTIMAL theory, autonomy, variable practice, schema theory

4.2 Introduction

The Optimizing Performance Through Intrinsic Motivation and Attention for Learning (OPTIMAL) theory (Wulf & Lewthwaite, 2016) endeavours to change the perspective for motor learning and performance theory by postulating central roles for motivation and attention in directing learning and performance outcomes. Traditional motor learning theories described performance and learning modulation caused by practice variables like feedback, practice variability, task difficulty, and movement observation through a cognitivist, information-processing lens (Adams, 1971; Gudagnoli & Lee, 2001; Salmoni, Schmidt, & Walter, 1984; Schmidt, 1975, Sternberg, 1969). In contrast, OPTIMAL theory posits that intrinsic motivation and focus of attention drive motor learning and performance differences as well as any information processing differences that may coincide (Wulf & Lewthwaite, 2016; Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015).

OPTIMAL theory proposes three primary factors that affect learning and performance: Autonomy, expectancies, and attentional focus. The focus of this experiment was on the autonomy factor. According to OPTIMAL theory, supporting the need for autonomy directly benefits motor learning and performance and enhances the expectancy of success by instilling a sense of agency in learners (Wulf & Lewthwaite, 2016). The most common method for satisfying the need for autonomy in the motor learning literature is to provide learners with choices during practice.

Learners have been provided with various types of choices in a corpus of research known as self-controlled learning (McKay, Carter, & Ste-Marie, 2014). Often, the choices are instructionally-relevant, for example learners have been asked to choose their feedback schedules (e.g., Janelle, Barba, Frehlich, Tennant, & Cauraugh, 1997), the practice schedule (Wulf & Adams, 2014; Wulf, Freitas, & Tandy, 2014), and when to use an assistive device (Wulf & Toole, 1999). There appears to be evidence of robust self-controlled learning benefits which the authors of OPTIMAL theory have argued are due to enhanced perceptions of autonomy support among learners (Wulf et al., 2017; Wulf & Lewthwaite, 2016). Conversely, a number of other explanations have been suggested for self-controlled learning benefits, including spontaneous differences in information processing (Carter & Ste-Marie, 2017). When self-controlled learning experiments provide learners choices over instructionally-relevant features of practice it may be impossible to separate motivational and information processing influences because relevant choices can be beneficial in multiple ways (Lewthwaite et al., 2015).

The strongest evidence in support of the OPTIMAL theory view that autonomy support enhances motor learning is supplied by experiments that provided learners with instructionally-irrelevant choices. In a pair of experiments, Lewthwaite and colleagues (2015) asked participants to choose which colour of golf balls to putt (Experiment 1) and which paintings to hang on the laboratory wall in addition to which activity they would like to do following a retention test (Experiment 2). A second group of participants were yoked to the choices made by the self-control groups in each experiment. The results demonstrated that providing learners with instructionally-irrelevant choices was sufficient to provide strong motor learning benefits. Lewthwaite and colleagues (2015, p. 1386) argued these experiments “appear to be among the first to provide *direct* evidence that giving learners choice per se can affect motor learning without providing content (e.g., demonstrations of the goal movement) or strategic learning advantages (emphasis theirs).” By providing instructionally-irrelevant choices, Lewthwaite and colleagues were able to avoid confounds present in previous self-controlled learning experiments and present evidence that autonomy support is sufficient to boost motor learning.

In a subsequent experiment, the OPTIMAL theorists and their colleagues reported that instructionally-irrelevant choices can be equally effective as instructionally-relevant choices (Wulf, Itwatsuki, Machin, Kellogg, Copeland, & Lewthwaite, 2017; Experiment 2). In the experiment, one group of participants was asked to choose which colour mat to place underneath a target that was to be lassoed. A second group was asked to choose when they wished to view an instructional video demonstrating proper lassoing technique and was yoked to the mat choices of the first group. Likewise, the first group was yoked to the video observation choices of the second group. A third group was yoked to both sets of choices. On a delayed 48-hour retention test both groups that were provided choices lassoed significantly more accurately than their counterparts in the yoked group. Importantly, the choice groups performed similarly on the retention test. Wulf and colleagues concluded that “the source of learner-controlled benefits is not related to the content of the choice per se but to the opportunity for choice and its consequences provided close to performance” (Wulf et al., 2017, p.5). Thus, autonomy support is thought to underlie self-controlled learning benefits in general, not simply when the choices are instructionally-irrelevant.

Although OPTIMAL theory does not include predictions explicitly pertaining to classically important motor learning variables such as feedback and practice schedule, self-controlled learning experiments have shown advantages when asking learners to control these features themselves and it has been argued that autonomy accounts for these benefits (e.g., Janelle et al., 1997; Wulf & Lewthwaite, 2016; Wu & Magill, 2011). Indeed, the authors of OPTIMAL theory recommend that coaches, instructors, and therapists ask learners to make these relevant choices during practice in order to support their need for autonomy (Wulf & Lewthwaite, 2016; Wulf, Shea, & Lewthwaite, 2010). Wulf and Lewthwaite (2016) describe the typical practice scenario as one where the coach or instructor makes all the instructionally-relevant choices, including what tasks to practice and when to provide feedback, and suggest this scenario can lead to a 'vicious cycle' of suboptimal learning and performance. In contrast, the optimal practice scenario is described as one where the learner makes choices, potentially resulting in a "virtuous cycle" of enhanced performance and learning, as well as enhanced perceptions of autonomy and expectancies.

If learners are asked to choose what tasks to practice it is possible they will choose to practice the same task repetitively, a schedule known as constant practice. Constant practice is hypothesized to be less effective for motor learning than a varied practice by the influential though moribund Schema theory and numerous experiments have supported this prediction (e.g., Chua, Dimapilis, Iwatsuki, Abdollahipour, Lewthwaite, & Wulf, 2019; Schmidt, 1975). Variable practice involves practicing multiple parameterizations of the same skill during practice and is predicted to enhance performance on a delayed transfer test involving novel, unpracticed parameterizations of the task (Schmidt, 1975). A limitation on the external validity of self-controlled practice schedule experiments is that yoking controls for the schedule chosen by self-controlling learners (e.g., Wu & Magill, 2011). Therefore, it is difficult to evaluate the recommendation to provide self-control over instructionally-relevant practice features such as practice schedule. The purpose of the present experiment was to fill this gap by independently testing the effects of autonomy support and practice schedule in a 2 X 2 factorial design. Conditioning on the prediction that all choices are equally effective, autonomy support was manipulated by either providing an instructionally-irrelevant choice or yoking to those choices, and practice schedule was manipulated by asking learners to practice in a constant or variable fashion. If asking learners to schedule their own practice is optimal for motor learning because it satisfies the need for autonomy, then participants who are provided with choices would be expected to learn more effectively than their yoked counterparts, regardless if they practice in a varied or constant fashion. Conversely, schema theory predicts that practice schedule is an important practice variable independent of motivation (Schmidt, 1975). Therefore, this experiment provides a test between OPTIMAL theory (recommendations) and schema theory.

Crossing practice schedule and autonomy support in a factorial design allows for a test of multiple core OPTIMAL theory predictions. In addition to predictions specific to autonomy support, OPTIMAL theory hypothesizes that *in general*, variables that benefit motor performance enhance learning as well, leading to the virtuous cycle of optimal learning described above (Wulf & Lewthwaite, 2016). Conversely, Kantak and Winstein (2012) have argued for a performance-learning distinction, suggesting that variables such as practice and feedback schedule can have inconsistent directional effects on learning and performance. While variable practice has frequently been shown to enhance motor learning (e.g., Chua et al., 2019; Kelso & Norman, 1978), the effect has not always been consistent from acquisition to transfer. For example, McCracken & Stelmach (1977) reported a significant practice schedule by time interaction, wherein participants were more effective during practice with a constant practice schedule yet less effective at transfer, relative to a group that followed a variable schedule. Therefore, in addition to testing the OPTIMAL theory recommendation to ask learners to choose which tasks to practice, this experiment also provides a test of the consistent-effects prediction (Wulf & Lewthwaite, 2016).

The core OPTIMAL theory hypotheses under scrutiny in the present experiment were: 1) autonomy support facilitates motor performance, defined here as mean acquisition performance 2) autonomy support facilitates motor learning, defined as delayed transfer performance 3) autonomy support enhances expectancies, defined as the scores on self-efficacy measures, 4) practice variables that optimize performance facilitate learning, defined as consistent effects during acquisition and transfer tests, and 5) the opportunity to make choices enhances perceptions of autonomy support, defined as the score on the Basic Needs Satisfaction in Sport Scale (BNSSS; Ng, Lonsdale, & Hodge, 2011). In addition, a prediction emanating from the practical recommendations in OPTIMAL theory was tested: autonomy support attenuates the effect of practice schedule on delayed transfer performance. In contrast, a competing prediction from schema theory was also tested: variable practice facilitates motor learning, defined as delayed transfer performance.

In order to test predictions above, participants were assigned to one of four groups: 1) autonomy and variable practice, 2) autonomy and constant practice, 3) yoked and variable practice, and 4) yoked and constant practice. The groups completed a pre-test followed by 12 acquisition blocks of throwing three darts with the non-dominant hand. Retention and transfer tests were conducted the day after acquisition. Participants in the variable practice groups threw darts to three different targets, switching targets following each practice block. The constant practice groups threw only to the central target during acquisition. Participants in the autonomy groups were asked to choose before each acquisition block from three sets of identical darts with different coloured flights, while their counterparts in the yoked groups were asked to follow the same flight-colour schedule.

4.3 Method

The experimental design and analysis was planned prior to data collection and made public on the Open Science Framework before viewing the data: https://osf.io/6x9j4. The full dataset is also available through this link.

4.3.1 Participants

An *a priori* power analysis was conducted using G*power software in order to determine the sample size required to achieve a power of .8 to detect a medium sized effect, *d* = .5. A minimum of *N* = 128 was required for the present experiment. Data were collected from 129 participants (73 females – one dropped out after Day 1) with an average age of 22.84 years (*SD* = 9.16). Participants had relatively little experience throwing darts with their dominant hand in the previous year, averaging 3.5 experiences (*SD* = 12.07). Participants were randomly assigned to one of four experimental conditions with two constraints: Groups were balanced for gender and the first two participants were assigned to the choice groups to allow for initial yoking and random assignment thereafter. All participants provided written informed consent in accordance with the policies of the University’s Research Ethics Board.

4.3.2 Task and materials

The experimental task was to throw darts with the non-dominant hand to targets on a 1.22m^2 corkboard from a distance of 1.99 meters. The corkboard included four targets: A central target (1.36m from the floor), a high left target (170.5m from floor, 25.5cm from center), a low right target (111.5cm from floor, 25cm from center), and a medium high right target used for the transfer test (145.5cm from floor, 26cm from center). Each target consisted of a single point in the center surrounded by three concentric circles with diameters of 4cm, 8cm, and 12cm. The goal of the task was always to hit the point in the center of the target with each dart throw.

Four questionnaires were used at different time-points in the experiment. First, a questionnaire containing questions concerning the participant's age, sex, the frequency of their dart throwing experiences in the past year and in the past five years, and their previous experience in sports requiring use of an implement was created to gather pertinent participant background information (demographic questionnaire). Second, the Basic Need Satisfaction in Sport Scale (BNSSS; Ng, Lonsdale, & Hodge, 2011) was adapted to measure autonomy need satisfaction. For the BNSSS, participants respond to ten statements using a 7-point Likert-type scale, with "not true at all" and "very true" anchoring 1 and 7 respectively. The items were designed to probe autonomy need satisfaction. Examples items are: "In this study, I get to make choices," "In this study, I get opportunities to make decisions," and "In this study, I feel I am doing what I want to be doing." Third, participant's self-efficacy for the dart-throwing task was assessed (self-efficacy questionnaire). Participants were asked, in a consecutive fashion, how many of their next nine dart throws they thought they would get inside the largest target circle, the middle circle, and the smallest circle. Finally, the fourth questionnaire was a one-item test to assess participants' opinions of the relevance of the colour of the dart flights on dart-throwing performance (relevance questionnaire). Participants rated their agreement to the statement: "The colour of the dart flight had an effect on my performance of the dart throwing task." using a 7-point Likert-type scale, wherein 1 was anchored with strongly agree, 4 with neither agree nor disagree, and 7 with strongly disagree.

4.3.3 Procedure

Prior to initiating this experiment a pilot study was conducted with *N* = 14. The purpose of the pilot study was to ensure the procedures were sufficient to generate evidence of learning from pre-test to post-test, improvement across acquisition blocks, and potentially demonstrate effects of the independent variables. Further, since throwing darts in general, and with the non-dominant arm in particular, can cause delayed-onset muscle soreness, it was important to strike a balance between enough practice trials to observe the effects of interest while also avoiding substantial soreness during post-testing. The results of the pilot study indicated that participants improved significantly from pre-test to post-test, showed improvement across acquisition blocks, and despite the small sample, there was a significant effect for the practice schedule independent variable on post-test performance. Participants did not report muscle soreness during post-testing. Buttressed by the pilot study, the following procedures were adopted in this experiment.

All participants completed the experiment in three phases: a) pre-test, b) acquisition, and c) post-tests. Prior to completing the pre-test, each participant was shown the task and it was explained that their goal for the pre-test was to hit the center target with each dart thrown. The researchers explained that all nine darts to be thrown were of the same size, weight, and model, with the only difference between them being the colour of the dart flights: Three darts had black flights, three had white, and three had red. Each participant was given a basic explanation about how and where to stand and was instructed to throw the darts with their non-dominant hand. Participants then completed a 9-trial pre-test, throwing first the three darts with black flights, then three trials with white flights, and lastly three with red flights. The X and Y coordinates of each dart thrown were measured by hand with the assistance of a permanent ruler across the top of the corkboard and a second 120cm right-angle ruler. Following the pre-test, each participant completed the demographics questionnaire, the self-efficacy questionnaire, and the BNSSS.

During the acquisition phase, participants were asked to complete 12 blocks of three dart-throws. Participants were assigned to one level of each independent variable, resulting in four different groups: (1) autonomy with variable practice, (2) autonomy with constant practice, (3) yoked with variable practice and (4) yoked with constant practice. Participants in the variable practice groups rotated through three targets during acquisition: The goal for the first block was to hit the center target, the second block was the top left target, the third was the bottom right target, and then the cycle began again at the center target on the fourth block. The constant practice groups always had the goal of hitting the center target for all 12 blocks of acquisition. Participants in the autonomy support groups were asked to choose the coloured set of darts they preferred to throw on each block of acquisition. Participants in the yoked groups were asked to throw darts using the same colour schedule as those chosen by a counterpart in the autonomy support group. Specifically, participants in the variable-practice-yoked group were each yoked to the colour choices of a counterpart in the variable-practice-autonomy group, and likewise for the participants in the constant practice groups. Immediately after completing the acquisition dart-throwing blocks, participants completed the self-efficacy questionnaire and BNSS measures a second time. In addition, they answered the single-item relevance questionnaire.

After an approximate 24-hour delay, participants returned to the laboratory for post-testing. First, participants completed the self-efficacy questionnaire assessing their confidence for the first retention test. They were then instructed that they were to throw nine darts for the center target, following the exact same procedure as the pre-test, including the colour order of dart flights. Following the retention test, participants were shown a new medium-high-right transfer target and were asked to complete another self-efficacy questionnaire pertaining to their next 9 dart-throws. Participants then completed nine trials with the goal of hitting the new transfer target. Following completion of the transfer test participants were thanked for their time and debriefed on the purpose of the experiment.

4.3.4 Data analysis

Schema theory makes predictions specific to transfer test performance while OPTIMAL theory does not discriminate between retention and transfer for any of its predictions. Therefore, transfer performance was the only delayed performance block included in the analyses. The OPTIMAL theory and schema theory hypotheses for learning outcomes were tested by submitting mean transfer test dart-throwing radial error data to a 2 (Practice schedule: variable vs. constant) X 2 (Autonomy: autonomy vs. yoked) analysis of covariance (ANCOVA) with centered pre-test radial error and gender included as covariates (Schneider, Avivi-Reich, & Mozuraitis, 2015). OPTIMAL theory and schema theory hypotheses related to directional effects of practice variables on both performance and learning were tested by submitting mean acquisition performance, collapsed across blocks, and transfer test radial error data to a 2 (Practice schedule) X 2 (Autonomy) X 2 (Time) ANCOVA with repeated measures on the final factor and centered pre-test radial error and gender included as covariates.

The OPTIMAL theory prediction that autonomy support enhances self-efficacy was tested by submitting the self-efficacy scale data to a two-way 2 (Autonomy) X 2 (Practice schedule) X 3 (Time point: end of acquisition, pre-retention, pre-transfer) ANCOVA with repeated measures on the final factor and baseline self-efficacy and gender included as covariates. The OPTIMAL theory prediction that choosing enhances autonomy need satisfaction was tested by submitting the mean end-of-acquisition BNSSS data to a 2 (Autonomy) X 2 (Practice schedule) ANCOVA with baseline mean BNSSS and gender included as covariates.

4.4 Results

4.4.1 Descriptive statistics. The descriptive statistics for each group's radial error can be seen in Table 4.1. In general, radial error decreased for all groups from pre-test to block 12, and from the delayed 24-hour retention test to the transfer test. Overall dart-throwing accuracy was improved on the 24-hour delayed post-tests relative to the pre-test, suggesting that the participants learned to perform the task more effectively. All groups except the constant-yoked group demonstrated increased BNSSS scores at the end of acquisition, relative to baseline. All groups showed an increase in self-efficacy at the end of acquisition that returned to near baseline levels prior to retention and dropped below baseline levels prior to transfer (see Table

4.2). Prior to inferential analyses, data were screened for univariate and multivariate outliers. Three outliers were detected and removed from the subsequent analyses of radial error data, and two outliers were removed from the analysis of self-efficacy data.[5]

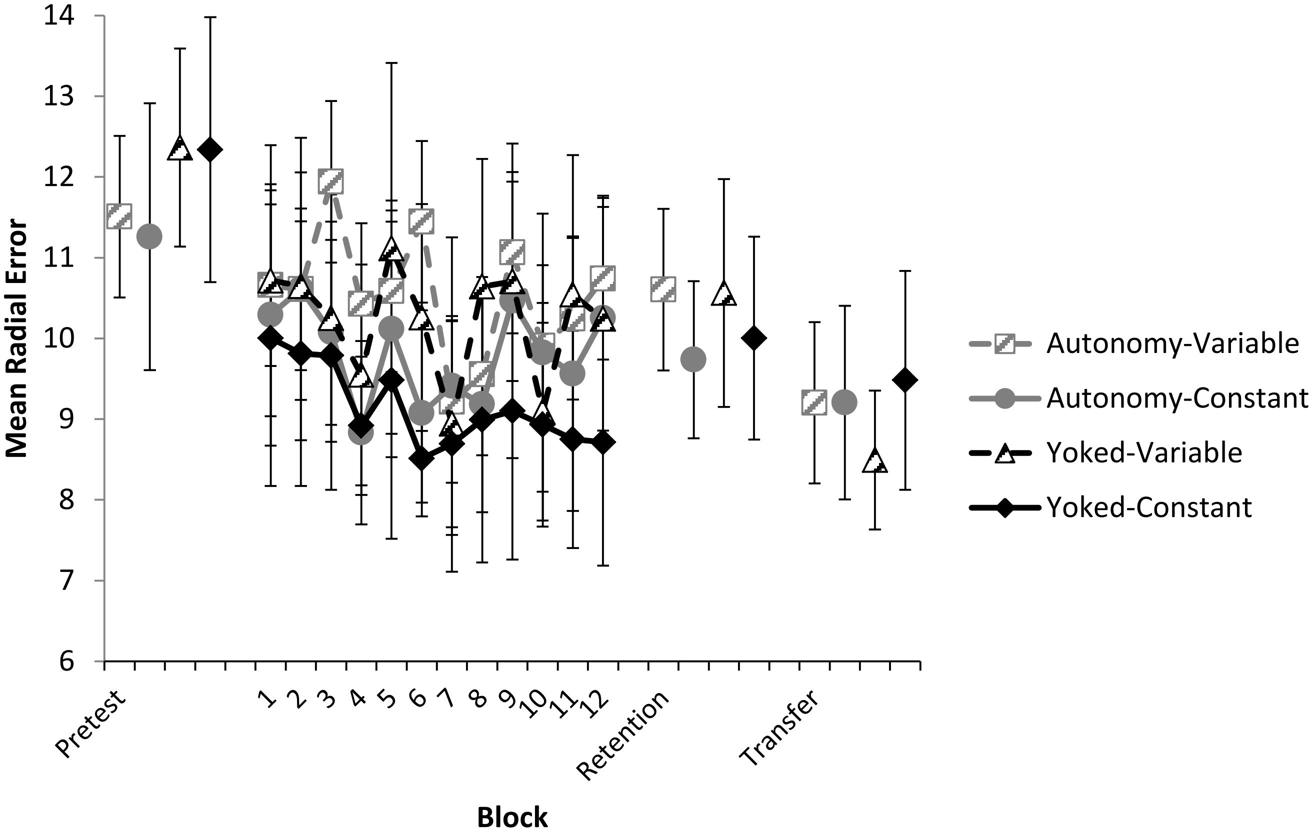

Figure 4.1 Dart throwing mean radial error on pretest, acquisition, retention, and transfer blocks. Error bars represent 95% confidence intervals.

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[5] To determine if the results were sensitive to the decision to delete outliers, performance data were log transformed and reanalyzed with the full sample. All statistical significance decisions were unchanged in the sensitivity analysis.

Table 4.1

Mean (SD) radial error (cm) for each group at pre-test, acquisition, retention and transfer.

Group	Pre-test	Acquisition	Retention	Transfer
Variable/ Autonomy	11.5(3.02)	10.53 (3.24)	10.60 (3.81)	9.20 (2.94)
Variable/ Yoked	12.37 (4.39)	10.23 (2.60)	10.56 (3.91)	8.49 (2.39)
Constant/ Autonomy	11.26 (4.50)	9.80 (2.90)	9.73 (2.65)	9.21 (3.27)
Constant/ Yoked	12.34(4.39)	9.14 (2.65)	10.00 (3.65)	9.48 (3.63)

4.4.2 Learning hypotheses. We tested the OPTIMAL theory prediction that the autonomy groups would perform more accurately on a delayed transfer test[6] than their yoked counterparts. After adjusting for gender ($r_{\text{partial}} = .128$, $p = .157$), and pre-test performance ($r_{\text{partial}} = .527$, $p < .001$; combined $r = .592$, $p < .001$), the yoked groups performed more accurately than the autonomy groups. These differences were not significant, however, as there was no main effect for autonomy, $F(1, 119) = 2.05$, $p = .155$ ($g = -.2$, $CI = -.49 - .08$). We also tested the schema theory prediction that the variable practice groups would perform more accurately than the constant practice groups on the delayed transfer test. Although the variable practice group performed more accurately than the constant practice group (see Table 4.1), the

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[6] Conducting the same analysis with retention data did not change any of the statistical significance decisions.

main effect of practice schedule was not statistically significant, *F*(1, 119) = 1.67, *p* = .199 (*g* = .19, *CI* = -.1 - .47). The Autonomy X Practice schedule interaction also failed to reach statistical significance, *F*(1, 119) = 1.03, *p* = .313.

4.4.3 Performance-learning hypotheses. We tested the OPTIMAL theory prediction that conditions that optimize dart throwing accuracy during acquisition would also facilitate enhanced accuracy on the transfer test (Figure 4.2). We also tested whether autonomy specifically would enhance both acquisition and transfer performance (Figure 4.3). After adjusting for gender (r_{partial} = .154, *p* = .087) and centered pre-test (r_{partial} = .514, *p* < .001; combined *r* = .588, *p* < .001), the yoked groups performed more accurately across both time points than their autonomy group counterparts. The main effect of autonomy was significant, *F*(1, 119) = 4.56, *p* = .038 (*g* = -.31, *CI* = -.59 - .02). The Autonomy X Time interaction was not significant, *F*(1, 119) = .231, *p* = .632. However, the Practice schedule X Time interaction was significant, *F(1*, 119) = 8.84, *p* =.005. Simple main effects analysis revealed that the variable practice groups performed significantly less accurately during acquisition than the constant practice groups, *F*(1, 119) = 4.12, *p* = .045, and non-significantly more accurately on the transfer test, *F*(1, 119) = 1.67, *p* = .199.

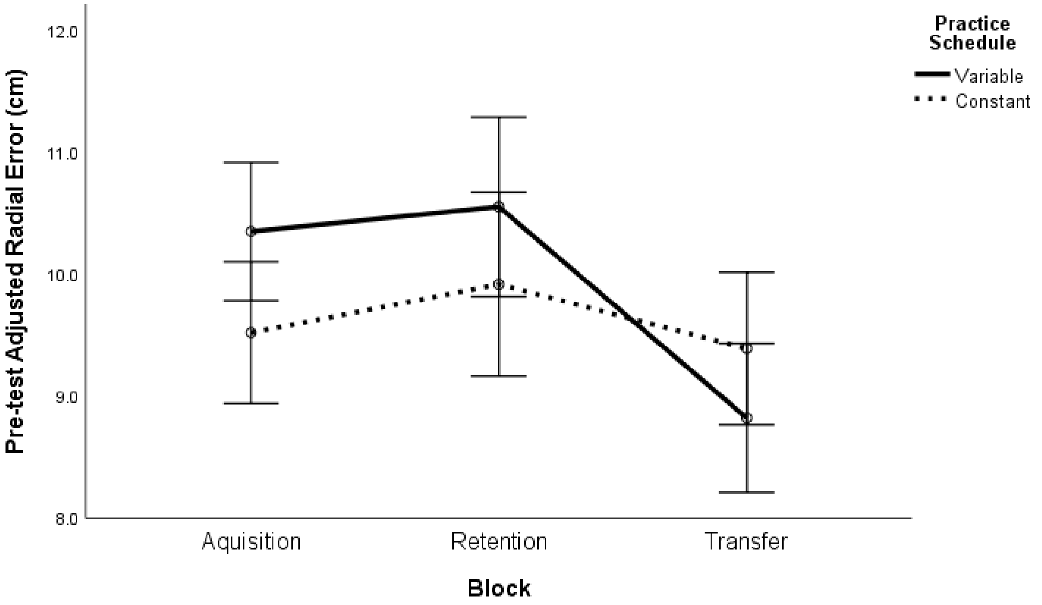

Figure 4.2. Mean radial error as a function of block and Practice schedule condition. Error bars represent 95% confidence intervals.

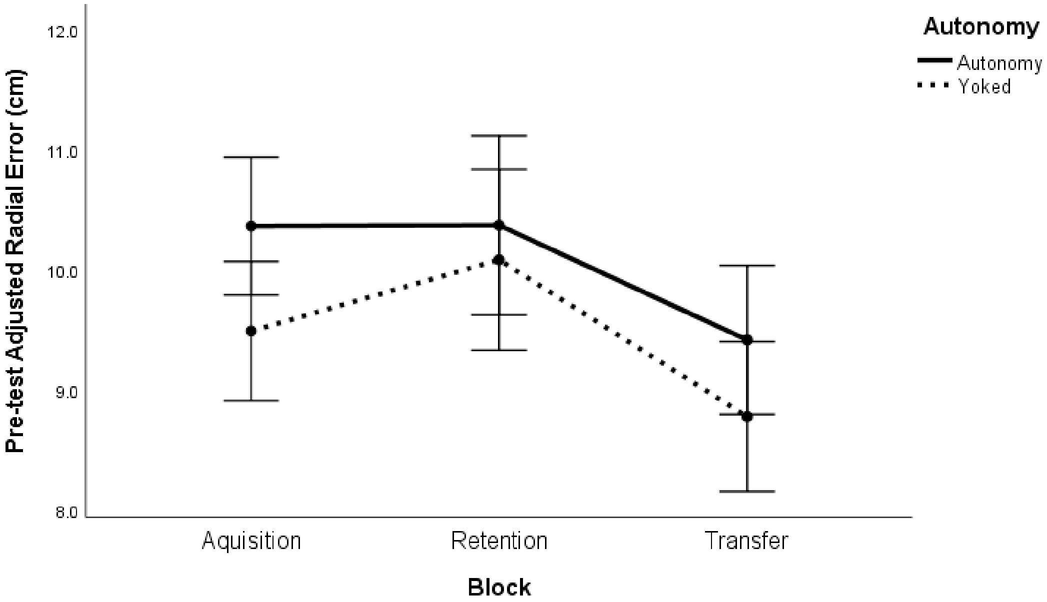

Figure 4.3. Mean radial error as a function of block and Autonomy condition. Error bars represent 95% confidence intervals.

4.4.4 Expectancies hypothesis. We tested the OPTIMAL theory prediction that the autonomy groups would report higher self-efficacy than the yoked groups. After adjusting for gender ($r_{\text{partial}} = .047$, $p = .603$) and centred baseline self-efficacy ($r_{\text{partial}} = .637$, $p < .001$), autonomy and yoked groups had nearly equivalent overall self-efficacy across measures, $F(1, 120) = .065$, $p = .80$ (see Table 4.2).

Table 4.2

Mean (SD) self-efficacy at pre-test, end of acquisition, retention, and transfer.

Group	Pre-test	End of Acquisition	Retention	Transfer
Variable/ Autonomy	1.67 (1.0)	2.02 (1.02)	1.60 (1.22)	1.15 (0.89)
Variable/ Yoked	1.62 (0.98)	1.98 (1.07)	1.68 (1.09)	1.32 (0.77)
Constant/ Autonomy	2.04 (1.16)	2.53 (1.14)	2.24 (1.08)	1.67 (0.99)
Constant/ Yoked	1.82 (1.13)	2.41 (1.26)	1.91 (0.94)	1.39 (0.95)

Note: Pre-test and end of acquisition self-efficacy measures were administered following putting performance; retention and transfer self-efficacy were administered prior to putting performance.

4.4.5 Perceived autonomy hypothesis. We tested the OPTIMAL theory prediction that autonomy groups would increase their perceived autonomy support at the end of acquisition more than the yoked groups. After adjusting for gender ($r_{partial} = .038$, $p = .670$) and baseline

BNSSS score ($r_{\text{partial}} = .608$, $p < .001$; combined $r = .618$, $p < .001$), the autonomy groups had higher BNSSS scores than the yoked groups and the difference was statistically significant, $F(1, 122) = 18.0$, $p < .001$.

4.5 Discussion

Wulf and Lewthwaite's (2016) OPTIMAL theory expanded the role of motivational variables in line with their critique that several legacy motor learning theories prioritized information processing and deemphasized the impact of motivation on motor learning and performance. The present experiment was designed to provide a pre-registered and high-powered test of core OPTIMAL theory predictions in addition to the practical recommendations generated by the theory. In particular, we investigated the effect of manipulating autonomy support on the acquisition and performance of a non-dominant arm dart-throwing task. To evaluate the recommendation that learners choose their own practice schedules in order to satisfy their need for autonomy, we conditioned on the prediction that all choices are equally effective and crossed autonomy support with practice schedule in a 2 X 2 factorial experiment.

OPTIMAL theory predicted that autonomy support would enhance performance, learning, and expectancies, and the recommendations in OPTIMAL theory imply that autonomy support would attenuate the effect of practice schedule. Further, OPTIMAL theory predicted that conditions that enhanced acquisition performance would also enhance transfer performance. In contrast, schema theory predicted that variable practice would result in more effective transfer test performance than a constant practice schedule (Schmidt, 1975). Despite evidence that making instructionally-irrelevant choices enhanced perceptions of autonomy support in the present experiment, none of the OPTIMAL theory predictions were supported. Rather than enhancing performance, autonomy support was an impediment to dart-throwing accuracy in this sample. Further, there was no evidence that autonomy support enhanced expectancies. Finally, despite leading to more accurate performance during acquisition, constant practice was did not enhance motor learning and the change in effectiveness across contexts was statistically significant. Therefore the prediction that, in general, conditions that enhance performance enhance learning was not supported.

The results of this experiment are in contrast to a number of previous experiments that have observed significant motor learning and performance benefits by providing instructionally-irrelevant choice (Abdollahipour et al., 2017; Chua et al., 2018; Lewthwaite et al., 2015; Wulf et al., 2014; Wulf et al., 2017). However, there have only been two experiments that have investigated instructionally-irrelevant choice with a pre-registered analysis plan, the present experiment included, and both have reported more effective performance by the yoked condition as compared to the choice condition (Grand et al., 2017). The largest sample size in a motor learning experiment that reported significant benefits of instructionally-irrelevant choice was *N* = 28 (Wulf et al., Experiment 1; choice vs. yoked comparison), while the pre-registered experiments have had sample sizes of *N* = 70 (Grand et al., 2017) and *N* = 128 (present experiment). Borrowing an analogy from Simonsohn (2015), if one astronomer reports a discovery observed through a small telescope but a second astronomer fails to observe the same discovery with a much larger telescope, the reliability of the first astronomer's discovery seems questionable. More concretely: the largest experiment reporting a significant benefit of providing instructionally-irrelevant choices on measures of motor learning had 33% power to detect an effect size of *d* = .596. Using the two-one-sided-test approach (Lakens, 2017; Simonsohn, 2015), the present experiment can reject learning effect sizes as large or larger than *d* = .596, *t*(122.96) = -1.437, *p* = .03. Therefore, the present results are substantially discordant with previous reports that instructionally-irrelevant choices have motor learning benefits.

The failure of the present experiment to support the schema theory prediction that a variable practice is more effective for motor learning than a constant practice also comes despite a more powerful design than most previous experiments (van Rossum, 1990). Nevertheless, the present experiment cannot rule out effects consistent with what has been previously reported in the variable practice literature. Some authors have argued practice schedule can have mixed effects (e.g., Ranganathan & Newell, 2013), with evidence that constant practice can be more beneficial when learning is assessed using the same parameters that were practiced (e.g., Breslin, Hodges, Steenson, & Williams, 2012). Although not part of the primary analysis in this experiment, an exploratory analysis revealed that the Practice schedule X Post-test interaction just failed to reach significance, *F*(1, 119) = 3.88, *p* = .051. In line with a putative "especial skill" effect (Breslin et al., 2012), the constant practice groups were more accurate on the retention test but less accurate on the transfer test. It seems more work is required to disentangle the myriad potential influences of practice schedule on motor learning.

With respect to the recommendation emanating from OPTIMAL theory that learners self-control their practice schedule, the present results do not support this advice. Practice schedule had observable effects that seemed to depend on the testing context while autonomy support was not helpful to performance at any time-point. It would seem more reasonable, based on these results, for a coach to carefully plan practice schedule while aiming to support autonomy with less consequential choices. Indeed, while the present experiment calls into question the effectiveness of providing autonomy support for enhancing motor learning and performance, the more general recommendation that coaches, instructors, and therapists support learners' autonomy by providing choices continues to have merit. A large body of evidence supports the notion that autonomy support is motivating to humans (Deci & Ryan, 2008; Patall et al., 2008). For example, when participants were given a choice over which order to complete strength and conditioning exercises, they performed significantly more repetitions of the exercises than a control group (Wulf et al., 2014). In applied settings, encouraging a greater volume of practice may be more important than enhancing the quality of the practice (Ericsson, Krampe, & Tesch-Romer, 1993).

To conclude, the present experiment featured a sample size based on *a priori* power calculations, making it larger than most motor learning experiments (Lohse, Buchanan, & Miller, 2016), and a pre-registered analysis plan that included prognostic covariates to improve the precision of estimated effects. Having adopted this rigorous experimental approach, both modern and legacy motor learning theories nevertheless failed to predict the results of this experiment, leading one to question current recommendations that emanate from motor learning research. Indeed, a recent large-scale collaborative effort to estimate the reproducibility of psychological research has reported that the effect sizes in replication attempts were on average half the size of the original effect and only 36% of replication attempts achieved a statistically significant result (Open Science Collaborative, 2015). As suggested by others, perhaps a deeper investigation of the motor learning and performance literature is warranted to determine the extent that research practices and selection effects have biased the evidence in favour of extant theory (Lohse, et al. 2016).

4.6 What Does the Article Add?

This article challenges the reliability of three OPTIMAL theory predictions pertaining to autonomy support. Autonomy support was detrimental rather than beneficial to dart throwing accuracy across acquisition and transfer. Further, autonomy support failed to enhance expectancies across all time points. This article also challenges the reliability of the OPTIMAL theory prediction that variables that optimize performance optimize learning. The observed interaction between performance and learning measures and practice schedule highlights the possibility that practice variables can impact learning and performance in different ways, in contrast to the OPTIMAL theory prediction. Finally, the recommendation that instructors ask learners to choose which tasks to practice appears to be less than optimal for motor learning and performance.

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5. Chapter 5

Elaborated Discussion of Article 2

The primary purpose of Experiment 2 was to test hypotheses generated by OPTIMAL theory and schema theory. As such, the number of analyses conducted were kept to a minimum (Lohse, Buchanan, & Miller, 2016). However, further post-hoc investigation of the data is useful to evaluate the robustness of the primary results. This general discussion will begin by reviewing sensitivity analyses before making some conclusions based on the findings from Experiment 2 and an introduction of the rationale for Study 3.

5.1 Sensitivity analyses

Although the data-analysis plan was pre-registered it was not the only possible approach to the data. Sensitivity analyses were conducted to evaluate how robust the primary findings were to key choices made in the planning stage. Three potentially influential choices that could have reasonably varied between researchers were: a) analyzing untransformed radial error scores and removing outliers from the analysis rather than conducting a log-transformation on the data, b) focusing exclusively on acquisition and transfer performance while ignoring performance on the retention test, and c) including pre-test performance as a covariate rather than as a within-subjects factor in a repeated measures analysis of variance (RM-ANOVA).

5.1.1 Log-transformed: The radial error data were inherently positive and as such appeared to be log-normally distributed. According to Shapiro-Wilk tests, the untransformed data significantly deviated from the normal distribution for each group at each of the primary time-points of interest: pre-test , acquisition, and transfer (all *p*s < .033). Following log-transformation, Shapiro-Wilk tests failed to detect significant deviation from normality at any time-point. Further, while screening for outliers in the untransformed data revealed three such deviant data points, no outliers were detected in the log-transformed data.

The log-transformed radial error data were submitted to the same primary analyses conducted on the untransformed data consistent with the pre-registered analysis plan. First, the log-transformed transfer data were analyzed in a 2 (Autonomy) X 2 (Practice schedule) analysis of covariance (ANCOVA) with log-transformed pre-test and gender included as covariates. Similar to the primary analysis, no significant main effects or interactions were detected in the log-transformed data (all *p*s > .129). Second, a 2 (Autonomy) X 2 (Practice schedule) X 2 (Time: acquisition, transfer) mixed ANCOVA with repeated measures on the final factor and log-transformed pre-test and gender included as covariates was conducted on the radial error data. The two significant results detected in the primary analysis were present in the log-transformed data as well. There was a significant main effect of choice, *p* = .032 and a significant Time X Practice schedule interaction, *p* = .007. Simple main effects revealed that the difference between the constant and variable practice groups at acquisition was not statistically significant in the log-transformed data, *p* = .085. The log-transformed sensitivity analysis suggests the results of the primary analyses are robust to the decision to use untransformed, non-normal data with outliers removed.

5.1.2 Including retention: Learning was defined exclusively as performance on the transfer test in Experiment 2 because schema theory specifically predicts that transfer performance is enhanced by variable practice. Further, OPTIMAL theory does not distinguish between retention and transfer as indices of motor learning. Nevertheless, retention test performance has emerged as the primary index of motor learning in modern research and the decision to focus exclusively on transfer performance may have influenced the results. As such, sensitivity analyses were conducted by substituting retention for transfer in the analysis of learning and by adding retention to the performance-learning analysis. Further, given log-normal nature of the radial error data, analyses were conducted on the log-transformed data as well.

A 2 (Autonomy) X 2 (Practice schedule) ANCOVA with pre-test and gender included as covariates was conducted on the retention test radial error data. As with the transfer test, there were no significant main effects or interactions, regardless if the data were raw or log-transformed. A 2 (Autonomy) X 2 (practice schedule) X 3 (Time: acquisition, retention, transfer) mixed ANCOVA with pre-test and gender included as covariates revealed a significant Practice schedule X Time interaction regardless if the data were raw or log-transformed (*p*s < .036). The significant reversal effect is specific to acquisition and transfer, as the constant practice groups maintained a non-significant advantage during retention.

The main effect of autonomy was not significant for the untransformed data, $p = .082$, but was significant for the log-transformed data, $p = .037$. In this case statistical significance is perhaps less relevant than the direction and size of the effect. Enhanced accuracy for the yoked group was not predicted by any paradigm and therefore rejecting the null hypothesis does not lead to accepting an alternate hypothesis predicting an advantage to being in a yoked group. Instead, the large discrepancy between the observed effect of providing an instructionally-irrelevant choice on motor performance and the predicted effect warrants the rejection of the

OPTIMAL theory hypothesis. This conclusion appears robust regardless if the retention test is included in the analysis.

5.1.3 Repeated measures ANCOVA: Although ANCOVA is the preferred approach to analysing pre-test post-test designs, many researchers choose to conduct a RM-ANOVA with pre-test and post-test included as levels of a within-subjects factor (Senn, 2007). Both analyses are technically valid but address slightly different questions. An ANCOVA compares differences at post-test conditional on equivalent pre-test performance, while RM-ANOVA analyzes the change from pre-test to post-test. In order to determine if the results observed in Experiment 2 were robust to model selection, the primary learning analysis was redone with pre-test included as a within-subjects factor. Since randomization was stratified by gender, gender was included in the analysis as a covariate. The analysis was repeated with the log-transformed data in addition to the raw data analyzed in the primary analysis.

A 2 (Autonomy) X 2 (Practice schedule) X 2 (Time: pre-test, transfer) mixed ANCOVA with repeated measures on the final factor and gender included as a covariate was conducted on the radial error data. There was a significant Autonomy X Time interaction, indicating that the yoked groups demonstrated a significantly greater reduction in error from pre-test to transfer, and this result was consistent for both raw and log-transformed data (*p*s = .038 and .035, respectively). None of the other interactions or main effects were significant.

The primary analysis failed to find support for the OPTIMAL theory hypothesis that providing autonomy support will enhance motor learning and the sensitivity analysis offers no relief.

5.1.4 Sensitivity analyses conclusions: The results of the sensitivity analyses support the robustness of the primary results. The negative effect of autonomy on motor performance does not appear to depend on the specific model selection chosen for the primary analysis. Further, the reversal effect from acquisition to transfer appears robust to model selection as well. With respect to the autonomy predictions, these results are in contrast to most of the extant literature with unidentified sources of variation responsible for the discrepancy. A rigorous examination of the evidence examining autonomy support and motor learning and performance is required to investigate when this effect is replicable, when it is not, and why.

While reversal effects are rare in the published literature, they appear more likely with practice and feedback scheduling interventions (Kantak & Winstein, 2012). The present experiment demonstrates a reversal effect in contrast to the OPTIMAL theory prediction and the result appears to be robust to some model selection and data treatment choices. OPTIMAL theory appears, at minimum, incomplete in regards to performance-learning dynamics.

5.2 Limitations

There were limitations to Experiment 2. First, the constant and variable groups differed with respect to the average distance of the acquisition targets from the transfer target. The constant group always threw darts to the central target, which was closer, on average, than the other two targets were to the transfer target. Although this confound can be removed by dividing the constant practice group into three subgroups, each practicing one of the targets, this procedure has drawbacks. Most important to the research questions in Experiment 2, it makes the retention test a transfer test for two of the constant subgroups. Since the retention test preceded the transfer test, this would have exposed two thirds of the constant group to a transfer task in between exposure to the independent variable and measurement of the focal learning measure. By allowing the constant group to practice a target that was closer to the transfer target, on average, the putative benefit of variable practice may have been attenuated. This is an issue of internal validity more than practical relevance; any variable practice will differ in average distance to any transfer target, save for experimentally contrived situations.

Another limitation, as with Experiment 1, is that the retention test and transfer test were not counterbalanced. Therefore it is difficult to determine if the transfer test was less difficult than the retention test, or if order effects are responsible for the apparent improvement in performance from one test to the next. Nevertheless, the purpose of Experiment 2 was to test the effect of practice conditions on measures of motor learning, not to test the difference between retention and transfer tests. The constant practice group was intentionally restricted to throwing only to the central target during acquisition, so having half of the participants in that condition complete a transfer test prior to a retention test would undermine the experimental manipulation being tested.

Third, infrequently participants would throw darts that did not stick in the corkboard and fell to the floor. These trials were repeated but the extra trials were not recorded. This was an infrequent occurrence but without data its impact is unmeasured.

5.3 General conclusions and moving forward

Experiment 2 produced evidence that offering learners instructionally-irrelevant choices enhanced their perceived autonomy but did not enhance expectancies or improve motor learning and performance. At present, these results are difficult to reconcile with the extant literature suggesting a positive impact of autonomy on motor learning and performance. Experiment 2, to our knowledge, was the largest self-controlled learning experiment yet to be conducted and employed a pre-registered analysis plan followed by sensitivity analyses of the main findings. Although the exact task and employed in Experiment 2 was unique, non-dominant throwing and choice over the colour of the object to be thrown have both been studied in previous experiments showing positive autonomy effects (e.g., Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015; Wulf, Chiviacowsky, & Drews, 2015). A meta-analytic treatment of the evidence may identify sources of heterogeneity in the effect of autonomy support on motor behaviour or discover sources of bias that cause the ostensible effect to be exaggerated in the literature. Without a rigorous investigation of the current evidence, the impact of autonomy on skilled motor performance appears uncertain in light of the present findings.

In the first two experiments of this dissertation the predicted benefit of providing autonomy support to learners has not been replicated, despite a substantial body of evidence suggesting the benefit of offering learners a choice is robust. In order to investigate the cause of this discrepancy, the third study of this dissertation is a meta-analysis of the self-controlled learning literature. The meta-analysis will address four questions that may help explain the failure to replicate in the first two experiments: 1) What is the average difference in means in self-control-to-yoked comparisons? 2) Is the effect of instructionally-irrelevant choice smaller than instructionally-relevant choice? 3) Is the effect of self-control smaller for discrete motor skills? 4) Has the effect of self-control been exaggerated in the literature by selection effects?

The purpose of this dissertation is to evaluate OPTIMAL theory and its implications for motor skill acquisition. The first two experiments call into question the applicability of OPTIMAL theory and its recommendations, at least pertaining to autonomy support. These results are inconsistent with the large body of evidence on which OPTIMAL theory predictions are based and as such further inspection of the extant evidence is necessary to evaluate both the results already described in this dissertation as well as the tenets of OPTIMAL theory. Given the concerns raised by Lohse and colleagues (2016) that motor learning research may be underpowered in general, we suspect the self-controlled learning literature may show similar weaknesses. Study 3 will be the final effort to understand the effect of autonomy support on motor learning, employing a meta-analysis as well as a p-curve (Simonsohn, Nelson, & Simmons, 2014) and weight-function modelling (Hedges & Vevea, 1996) to investigate potential selection effects and account for them when estimating the effect of autonomy.

6. Chapter 6

Article 3: Self-controlled motor learning: A meta-analysis.[7]

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[7] A version of this manuscript will be submitted for publication:
McKay, B., Yantha, Z., Hussein, J, Carter, M.J., & Ste-Marie, D. M.(in preparation) Self-controlled motor learning: A meta-analysis

6.1 Abstract

The self-controlled motor learning literature consists of experiments that compare a group of learners who are provided with a choice over an aspect of their practice environment to a group who are yoked to those choices. A qualitative review of the literature suggests an unambiguous benefit from self-controlled practice. A meta-analysis was conducted on the effects of self-controlled practice on retention test performance measures with a focus on assessing and potentially correcting for selection bias in the literature, such as publication bias and *p*-hacking. First, a naïve random effects model was fit to the data and a moderate benefit of self-controlled practice, g = .43 (k = 56, N =2251, 95%CI; .31 - .55) was displayed. Second, publication status was added to the model as a potential moderator, revealing a significant difference between published and unpublished findings, with only the former reporting a benefit of self-controlled practice. Third, to investigate and adjust for the impact of selectively reporting statistically significant results, a weight-function model was fit to the data with a one-tailed *p*-value cutpoint of .025. The weight-function model revealed substantial selection bias and estimated the true average effect of self-controlled practice as g = .13 (95%CI: - .07 - .33). In parallel, *p*-curve analyses were conducted on the statistically significant results published in the literature and the outcome suggested a lack of evidential value. Fourth, a suite of sensitivity analyses were conducted to evaluate the robustness of these results, all of which converged on trivially small effect estimates. Overall, our results suggest the benefit of self-controlled practice on motor learning is small and not currently distinguishable from zero.

Keywords: motor learning; self-controlled learning, OPTIMAL Theory; meta-analysis, publication bias

6.2 Introduction

Asking learners to control an aspect of their practice environment – any aspect – has come to be known as self-controlled practice in the motor learning literature (Sanli, Patterson, Bray, & Lee, 2013; Wulf & Lewthwaite, 2016). The first published experiments to test self-controlled learning asked learners to control their augmented feedback schedule (Janelle, Kim, & Singer 1995; Janelle, Barba, Frehlich, Tennant, & Cauraugh, 1997). For example, in an experiment by Janelle and colleagues (1997), participants practiced throwing tennis balls at a target with their non-dominant hand. The practice period occurred over two separate days. Participants were assigned to one of four experimental groups (*n* = 12): Self-controlled knowledge of performance (KP), yoked-to-self-control, summary KP after every 5 trials, and no KP control group. The self-controlled group could request KP whenever they wanted it, while each yoked group participant was matched with a self-control group counterpart and received KP on the same schedule. The experimenter evaluated the participants' throws, identified the most critical error in their throwing form, and provided KP via video feedback, along with directing attention to the error and giving prescriptive feedback. During a delayed-retention test, the accuracy, form, and speed of the throw were assessed. The results indicated that the self-control group threw more accurately and with better form than all other groups on the retention test. The self-control and yoked groups did not significantly differ in throwing speed, but the control group threw faster than the self-control group on the second retention block. The results were interpreted as evidence that the participants provided with choice were able to process information more efficiently than their counterparts who received a fixed schedule of feedback.

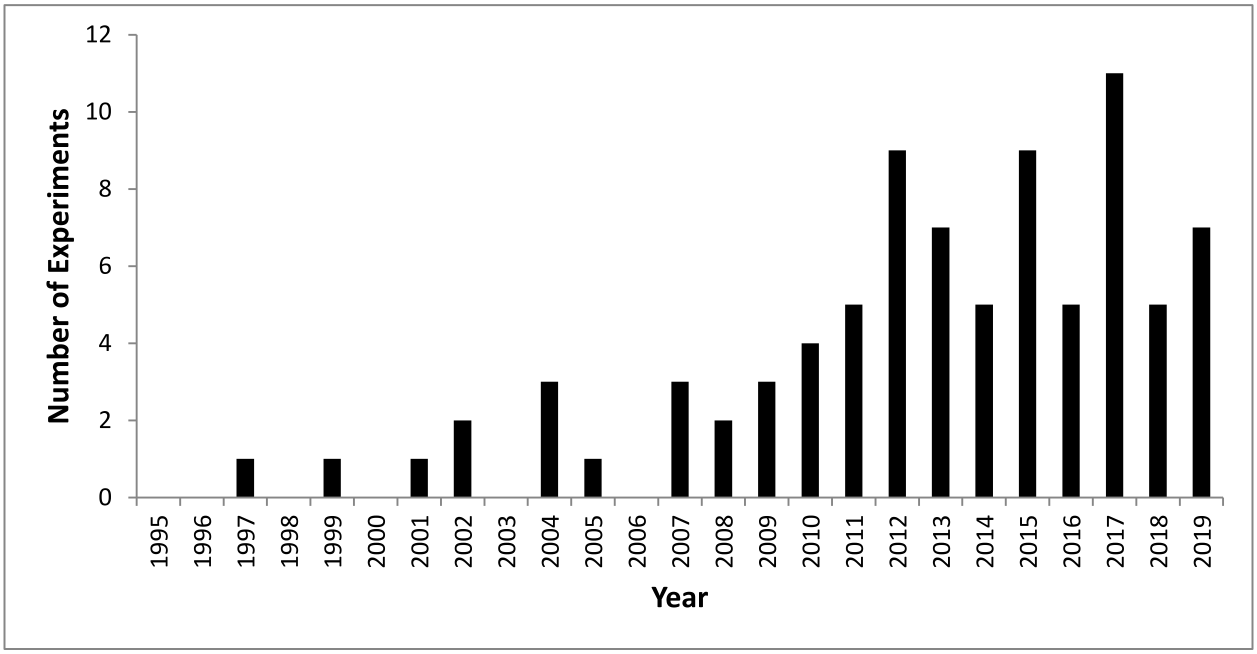

Figure 6.1. Number of self-controlled learning experiments meeting our inclusion criteria by year.

The number of experiments comparing self-controlled-learning participants to yoked groups has been increasing in the time since the original experiments by Janelle and colleagues (Janelle et al., 1995; 1997; see Figure 1). Researchers have experimented with giving learners control over a variety of variables in the practice environment. A qualitative assessment of the literature suggests that self-control is generally beneficial regardless of choice-type (Wulf & Lewthwaite, 2016). For example, self-control has been effective when participants have been provided choice over what can be considered instructionally-relevant variables such as: knowledge of results (KR; Chiviacowsky & Wulf, 2002), KP (Lim, Ali, Kim, Kim, Choi, & Radlo, 2015), concurrent feedback (Huet, Camachon, Fernandez, Jacobs, & Montagne, 2009), use of an assistive device (Wulf, Clauss, Shea, & Whitacre, 2001), observation of a skilled model (Lemos, Wulf, Lewthwaite, & Chiviacowsky, 2017), practice schedule (Wu & Magill, 2011), practice volume (Lessa & Chiviacowsky, 2015), and task difficulty (Leiker, Bruzi, Miller, Nelson, Wegman, & Lohse, 2016). Additionally, self-controlled benefits have also been found for instructionally-irrelevant variables – like the colour of various objects in the practice environment (Wulf, Iwatsuki, Machin, Kellogg, Copeland, & Lewthwaite, 2017), other decorative choices, and the choice of what to do after the retention test is complete (Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015).

Despite the widespread optimism that self-controlled practice is useful for enhancing motor learning, researchers continue to debate the underlying mechanisms responsible for the effect (Carter & Ste-Marie, 2017b; Wulf, et al., 2017). Beginning with Janelle and colleagues (1995), both motivational and information processing mechanisms were proposed as possible explanations for self-control benefits. Researchers have since supported these two mechanisms and, from a motivational perspective, have posited that self-control enhances confidence (Janelle et al., 1995; Chiviacowsky, Wulf, & Lewthwaite, 2012; Wulf & Lewthwaite, 2016) and satisfies the basic psychological need for autonomy (Sanli et al, 2013; Wulf & Lewthwaite, 2016), motivating motor performance and learning enhancement. Most self-controlled learning experiments, however, have involved participants making choices over potentially informative variables, which could act as a confounding variable. Citing this potential motivational/informational confound, Lewthwaite and colleagues (Lewthwaite et al., 2015) experimented with providing instructionally-irrelevant choices, such as the colour of the golf balls to putt, the painting to hang on the wall, and what to do following the retention test. Lewthwaite and her colleagues reasoned that information processing explanations could not account for benefits due to these incidental choices, and instead motivational factors would be more likely. Consistent with the motivational hypothesis, participants exhibited significantly greater motor learning on a golf putting (Experiment 1) and balance task (Experiment 2). Subsequently, several experiments have reported benefits with instructionally-irrelevant choices (Abdollahipour, Nieto, Psotta, & Wulf, 2017; Chua, Wulf, & Lewthwaite, 2018; Halperin, Chapman, Martin, Lewthwaite, & Wulf, 2016; Iwatsuki, Navalta, & Wulf, 2019; Wulf, Chiviacowsky, & Cardozo, 2014; Wulf et al., 2017), further reinforcing this motivational perspective.

A contrasting line of research has been reported by Carter and his colleagues (Carter, Carlsen, & Ste-Marie, 2014; Carter & Ste-Marie, 2017a; Carter & Ste-Marie, 2017b) in which informational factors, the second dominant perspective, are given more weight as an explanatory variable. In one experiment (Carter, et al., 2014), for example, self-control participants were provided with choice over receiving KR, but divided into three experimental groups; those who could receive KR: before the trial, after the trial, or both (they would decide before, but could change their mind following the trial). Timing of the choice significantly attenuated the self-control benefit. While the self-after and self-both groups exhibited learning advantages relative to yoked counterparts, the self-before group displayed no such advantage. The argument proffered by the researchers was that there was more informational value to be gained from KR requested after a trial than when it had to be requested before the outcome of the trial occurred. In another experiment, asking learners to complete an interpolated activity in the interval preceding their choice of whether to receive KR significantly attenuated the self-control benefit (Carter & Ste-Marie, 2017a). As a final example, a third experiment compared an instructionally-relevant choice group (i.e., when to receive KR) - to an instructionally-irrelevant choice group (i.e., - which video game to play after retention and which colour arm wrap to wear while practicing; Carter & Ste-Marie, 2017b). Unlike a similar experiment by Wulf and colleagues (2017), Carter and Ste-Marie found that instructionally-relevant choices were more effective than instructionally-irrelevant choices. Overall, they have used these different findings to tie self-controlled learning benefits to information-processing activities of the learner and, in particular, those related to the processing of intrinsic feedback (e.g., Chiviacowsky & Wulf, 2005; Carter & Ste-Marie, 2017a) and the provided KR (e.g., Grand, Bruzi, Dyke… et al., 2015).

In this research, these different viewpoints concerning the mechanisms of self-controlled learning advantages were examined via meta-analysis with choice-type included as a moderator. The logic was that the motivational and informational perspectives would have different predictions. More specifically, from a motivation hypothesis, no moderating effect of choice-type on motor learning would be expected. In contrast, smaller effects for irrelevant-choice type, as compared to relevant-choice type would be expected from the information-processing perspective. Although researchers have asked a variety of research questions involving the self-controlled learning effect, many experiments have shared four important features: 1) a group in which participants are asked to make at least one choice 2) a comparison group that is yoked to those choices 3) a delayed 24-hour (or greater) retention test, and 4) an objective measurement of motor performance. This commonality across the experiments thus allowed for the meta-analysis to be conducted with these four features as critical inclusion criteria[8].

Beyond this interest in the possible theoretical mechanisms, a more important question addressed was whether there is in fact evidential value for the self-controlled learning benefit. This is of relevance because the current consensus in the field is that self-controlled practice is generally more effective than yoked practice (for reviews, see Sanli et al., 2013; Ste-Marie, Carter, & Yantha, in press; Wulf & Lewthwaite, 2016; Wulf, Shea, & Lewthwaite, 2010). Reflecting this confidence in its benefits for motor learning, researchers have recommended adoption of self-control protocols in medical training (Brydges, Carnahan, Safir, Dubrowski, 2009; Jowett, LeBlanc, Xeroulis, MacRae, & Dubrowski, 2007; for a review, Wulf et al., 2010), physiotherapy (Hemayettalab, Arabameri, Pourazar, Ardakani, & Kashefi, 2013; for a review, Wulf, 2007), music pedagogy (for a review, Wulf & Mornell, 2008), strength and conditioning (for a review, Halperin, Wulf, Vigotsky, Shoenfeld, & Behm, 2018), and sports training (Janelle et al., 1995; for a review, Sigrist, Rauter, Riener, & Wolf, 2013).

Problematic though is that recent, high-powered experiments with pre-registered analysis plans have failed to observe motor learning or performance benefits with self-control protocols (Grand, Daou, Lohse, & Miller, 2017; McKay & Ste-Marie, 2019; Yantha & Ste-Marie, 2019). Against the backdrop of the so-called replication crises in psychology (Open Science Collaboration, 2015), there is reason for pause when evaluating the ostensible benefits of self-controlled learning. There have been no pre-registered positive results to date. Further, Lohse,

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[8] Additional moderators associated with discrete differences in experimental protocol were also included in the analysis, along with publication status. Choice-type, however, is the most theoretically relevant of the moderators and thus for brevity is the only one discussed outside the methods and results sections.

Buchanon, & Miller (2016) have raised concerns about publication bias, uncorrected multiple comparisons, *p*-hacking, and other selection effects in the motor learning literature. Therefore, in order to address the impact of selection effects on estimates of the self-controlled learning effect, a weight function model (Carter, Schönbrodt, Gervais, & Hilgad, 2019; Hedges & Vevea, 1996; Vevea & Hedges, 1995; Vevea & Woods, 2005; McShane, Böckenholt, & Hansen, 2016) with a one-tailed *p*-value cutpoint of .025 was fit to the dataset of effects to provide a pre-registered adjusted estimate of the overall self-controlled learning effect. Even the adjusted estimate is biased if the data generating processes are biased in ways not captured by the assumptions of the model, so further sensitivity analyses were conducted to estimate the average effect of self-control after correcting for selection effects (Carter et al., 2019; Vevea & Woods, 2005). In parallel, in an effort to investigate the presence of evidential value in the literature, significant results were subjected to a *p*-curve analysis (Simonsohn, Nelson, & Simmons, 2014a; Simonsohn, Simmons, & Nelson, 2015). The *p*-curve analysis focuses exclusively on significant results and therefore is not affected by publication bias.

In sum, the objective of this meta-analysis was to estimate the true average effect of self-controlled learning and evaluate the evidential value of the self-controlled learning literature. Bias resulting from selective publication and *p*-hacking were assessed with weight function and *p*-curve models and effect size estimates were adjusted accordingly. A key theoretical question was also addressed through moderator analyses, but, to anticipate, inferences will depend on the reliability of the evidence overall. Finally, sensitivity analyses were conducted in addition to pre-registered analyses in an effort to understand the extent that the conclusions depended on the modelling techniques and assumptions adopted.

6.3 Method

6.3.1 Pre-registration: The procedures followed to conduct this meta-analysis were pre-registered and can be viewed at https://osf.io/qbg69. This meta-analysis was retrospective and earlier samples of the literature had been meta-analyzed prior to this pre-registration, albeit with different data-collection procedures, scope, and excluding recent experiments.

6.3.2 Literature search: The literature search and data extraction were conducted by three authors (BM, ZY, JH) and one research assistant (HS) independently. The goal of the search was to identify all articles that meet the inclusion criteria for the meta-analysis. Specifically, randomized experiments were subject to five criteria for inclusion: 1) A self-control group in which participants were asked to make at least one choice during practice, 2) a yoked-group that experienced the same practice conditions as the self-controlled group, 3) a delayed ~24-hour retention test or test with longer delay interval, 4) an objective measurement of motor performance, and 5) publication in a peer-reviewed journal or acceptance as part of a Master's or PhD thesis.

The search commenced at PubMed and Google Scholar with the following query: "self-control* OR self-regulat* OR self-direct* OR learner-control* OR learner-regulat* OR learner-direct* OR subject-control* OR subject-regulat* OR subject-direct* OR performer-control* OR performer-regulat* OR performer-direct* AND motor learning." The query retrieved 9014 hits on PubMed and 98,600 hits on Google Scholar. Each researcher excluded hits based on title alone or title and abstract when necessary and quit searching the databases at self-selected intervals following extended periods of excluding 100% of search results. Following an initial run of searching data bases, each researcher employed their own search strategies, including reviewing the reference sections of reviews and included articles, consulting the OPTIMAL theory website: https://optimalmotorlearning.com/index.php/did-you-know-that/, and searching the ProQuest Thesis database.

This literature search process resulted in 160 articles that could not be excluded without consulting the full-text of the article. All 160 articles were coded for inclusion or exclusion by two researchers independently. All instances of disagreement between coders were reviewed by three authors (BM, ZY, and JH), and consensus was reached in each case. Disagreements were infrequent and were often caused by a lack of clarity in the articles (e.g., 100%-KR groups labelled as yoked groups). None of the coding disagreements evolved into conceptual disagreements. Rather, in each case, it was identified that one coder had missed a detail in the full text that changed its inclusion eligibility. Subsequent to this process, a total of 60 articles, which included 79 experiments, met the inclusion criteria.

6.3.3 Data extraction: The four researchers broke off into pairs and half the included experiments were independently coded by one pair, with the other half coded by the other pair. The coding included varied moderators, extracted publication year, and sample size. Also Hedges' *g* was calculated from reported statistics and sample size using the 'compute.es' package in R. Effect sizes were calculated from means and standard deviations, test statistics like *t* and *f*, or from precisely reported *p*-values. When covariates were included in the analysis, the correlation coefficient for the covariate - dependent measure relationship was required to calculate accurate effect sizes. Since this information is often not reported, authors were contacted and the information was requested. One effect size was calculated for each of three time points for each experiment: Acquisition, retention, and transfer. Often, multiple dependent measures were reported in the same experiment. The focus of this meta-analysis was on performance outcomes associated with the goal of the skill. The primary theoretical perspectives offered as an account for self-controlled learning are likewise focused on performance outcomes. For example, the OPTIMAL theory proposes that a learner's movements become coupled with the goal they are trying to achieve when they experience autonomy support during practice (Wulf & Lewthwaite, 2016). To reflect this focus, a dependent measure priority list was developed that gave higher priority to absolute error measures and less priority to consistency measures, time/work measures, and form scores. Dependent measure priority was ordered as follows: 1) absolute error (and analogous measures: radial error, points in an accuracy measure), 2) root-mean-square-error (RMSE), 3) absolute constant error, 4) variable error, 5), movement time (and distance travelled), 6) movement form – expert raters, 7) otherwise unspecified objective performance measure reported first in research report[9]. In the event that multiple measures of motor performance were reported for an experiment, effect sizes were calculated for the highest priority measure reported in the study. In experiments with multiple self-control groups and one yoked group, the self-control groups were combined (Higgins & Green, 2011). If multiple choice-types or sub-populations were included in an experiment, combined and individual effects were calculated for inclusion in moderator analyses.

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[9] Radial error, accuracy points, and distance travelled were added to the pre-registered dependent measures as they arose during data-extraction. Decisions were made blind to the data by an author not involved in said extraction (BM or DSM).

The independent data extractions were compared and inconsistent results were highlighted. There was 89% absolute agreement between pairs of coders on 1344 data points. For those with disagreement, one of the researchers from the other coding pair reviewed the relevant experiment to confirm the value to be used in the analysis. On one occasion, the third researcher was unable to match either effect calculation, so the involved researchers discussed the issue, determined the source of the inconsistency, and asked a fourth researcher to recalculate the effect size with clear instructions for avoiding confusion. The source of inconsistency was simply a rounding error when combining multiple groups.

Several articles failed to report the data necessary to calculate effect sizes at some or all time-points. A total of 39 authors were emailed with requests for missing data and 17 were able to provide data following a minimum one month period following the request. After requesting missing data, 23 experiments were excluded from primary analyses for missing retention data. Effects from a total of 56 experiments from 50 articles were included in the primary meta-analysis.

In addition to extracting effect sizes, inferential statistics were scraped from published experiments that reported a statistically significant effect at retention. Two authors (BM and JH) independently completed a *p*- curve disclosure form consisting of a direct quote of the stated hypotheses for each experiment, the experimental design, and a direct quote of the results indicating a significant result (see Appendix). There was 94% absolute agreement between the independent forms. Mismatches were resolved with consensus.

Table 6.1

Experiment characteristics and moderator coding.

Author	Year	setting	comp	choice	pub	subpop	interval	N
Aiken et al.	2012	applied	nomen	observe	y	adult	24	28
Alami	2013	lab	nomen	KR	n	adult	24	22
Ali et al.	2012	lab	yes	KR	y	adult	24	48
Andrieux et al	2016	lab	nomen	difficulty	y	adult	24	48
Andrieux et al.	2012	lab	nomen	difficulty	y	adult	24	38
Arsal	2004 (Exp. 1)	lab	nomen	KR	n	adult	48	28
Arsal	2004 (Exp. 2)	lab	nomen	KR	n	child	48	28
Barros	2010 (blked)	lab	nomen	KR	n	adult	24	48
Barros	2010 (rand)	lab	nomen	KR	n	adult	24	48
Barros et al.	2018 (Exp. 1)	labapplied	no	KR	y	adult	24	60
Barros et al.	2018 (Exp. 2)	lab	no	KR	y	adult	24	60
Bass	2015	lab	no	KR	n	adult	24	20
Bass	2018	applied	no	KR	n	adult	24	60
Brydges et al.	2009	applied	nomen	observe	y	adult	longer	48
Bund & Weimeyer	2004	labapplied	no	observe	y	adult	24	52
Carter & Patterson	2012	lab	nomen	KR	y	adult	24	20
Carter & Patterson	2012	lab	nomen	KR	y	older	24	20
Carter & Patterson	2012	lab	nomen	KR	y	two	24	40
Carter & Ste-Marie	2017 (a)	lab	no	KR	y	adult	24	44
Carter & Ste-Marie	2017 (b)	lab	no	incidental	y	adult	24	36
Carter & Ste-Marie	2017 (b)	lab	no	KR	y	adult	24	36
Carter & Ste-Marie	2017 (b)	lab	no	two	y	adult	24	54
Carter et al.	2017	lab	no	KR	y	adult	24	44
Carter et al.	2014	lab	no	KR	y	adult	24	48
Chen et al.	2002	lab	yes	KR	y	adult	48	48
Chiviacowsky	2014	lab	nomen	KR	y	adult	24	28
Chiviacowsky & Lessa	2017	lab	nomen	KR	y	older	48	22
Chiviacowsky & Wulf	2002	lab	nomen	KR	y	adult	24	30
Chiviacowsky	2012	lab	nomen	KR	y	clinical	24	30

Author	Year	setting	comp	choice	pub	subpop	interval	N
et al.								
Chiviacowsky et al.	2008	lab	nomen	KR	y	child	24	26
Chiviacowsky et al.	2012	lab	nomen	assistive	y	clinical	24	28
Davis	2009	applied	nomen	KP	n	adult	24	24
Fagundes et al.	2013	labapplied	nomen	model	y	adult	48	52
Fairbrother et al.	2012	lab	nomen	KR	y	adult	24	48
Ferreira et al.	2019	lab	nomen	KR	y	adult	24	60
Figueiredo et al.	2018	lab	no	KR	y	adult	24	30
Ghorbani	2019 (Exp .2)	labapplied	nomen	KR	y	adult	24	36
Grand et al.	2015	lab	no	KR	y	adult	24	36
Grand et al.	2017	lab	yes	incidental	y	adult	longer	68
Hansen et al.	2011	lab	no	KR	y	adult	24	24
Hartman	2007	lab	nomen	assistive	y	adult	24	18
Hemayettalab et al.	2013	lab	nomen	KR	y	clinical	24	20
Ho	2016	lab	nomen	amount	n	adult	24	120
Holmberg	2013	labapplied	no	KP	n	adult	24	24
Huet et al.	2009	labapplied	nomen	concurrent	y	adult	24	20
Ikodome et al.	2019 (Exp. 1)	labapplied	no	incidental	y	adult	24	40
Ikodome et al.	2019 (Exp. 2)	labapplied	no	observe	y	adult	24	40
Jalalvan et al.	2019	labapplied	nomen	difficulty	y	adult	24	60
Janelle et al.	1997	labapplied	yes	KP	y	adult	longer	48
Jones	2010	lab	yes	schedule	n	adult	24	40
Kaefer et al.	2014	lab	no	KR	y	adult	24	56
Keetch & Lee	2007	lab	yes	schedule	y	adult	24	96
Kim et al.	2019	lab	yes	KR	y	adult	24	42
Leiker et al.	2016	labapplied	nomen	difficulty	y	adult	longer	60
Leiker et al.	2018	lab	nomen	difficulty	n	adult	longer	60
Lemos et al.	2017	applied	no	observation	y	child	24	24
Lessa & Chiviacowsky	2015	applied	nomen	amount	y	older	48	36
Lewthwaite et al.	2015 (Exp. 1)	labapplied	nomen	incidental	y	adult	24	24
Lewthwaite et al.	2015 (Exp. 2)	lab	nomen	incidental	y	adult	24	30
Lim et al.	2015	applied	nomen	KP	y	adult	24	24
Marques & Correa	2016	applied	nomen	KP	y	adult	48	70
Marques et al.	2017	applied	nomen	KP	y	adult	24	30
Norouzi et al.	2008	lab	nomen	KR	y	adult	24	45

Author	Year	setting	comp	choice	pub	subpop	interval	N
Nunes et al.	2019	labapplied	no	KP	y	older	24	40
Ostrowski & Porter	2015	lab	nomen	KR	n	adult	24	80
Patterson & Carter	2010	lab	yes	KR	y	adult	24	24
Patterson & Lee	2010	labapplied	yes	difficulty	y	adult	48	48
Patterson et al.	2013	lab	yes	KR	y	adult	24	48
Patterson et al.	2011	lab	yes	KR	y	adult	24	60
Post et al.	2016	labapplied	no	KP	y	adult	24	44
Post et al.	2011	applied	no	amount	y	adult	24	24
Post et al.	2014	applied	nomen	amount	y	adult	24	30
Rydberg	2011	applied	nomen	schedule	n	adult	24	16
Sanli & Patterson	2013 (adult)	lab	no	schedule	y	adult	24	24
Sanli & Patterson	2013 (child)	lab	no	schedule	y	child	24	24
Ste-Marie et al.	2013	applied	no	KP	y	child	24	60
Tsai & Jwo	2015	lab	yes	KR	y	adult	24	36
von Lindern	2017	lab	nomen	KR	n	adult	24	48
Williams et al.	2017	lab	yes	concurrent	y	adult	24	29
Wu & Magill	2011	lab	no	schedule	y	adult	24	30
Wu	2007 (Exp. 1)	labapplied	yes	schedule	n	adult	24	30
Wulf & Adams	2014	lab	no	schedule	y	adult	24	20
Wulf & Toole	1999	labapplied	yes	assistive	y	adult	24	26
Wulf et al.	2015	labapplied	no	schedule	y	adult	24	68
Wulf et al.	2001	labapplied	yes	assistive	y	adult	24	26
Wulf et al.	2017 (Exp. 1)	labapplied	no	incidental	y	adult	24	32
Wulf et al.	2017 (Exp. 2)	labapplied	no	incidental	y	adult	48	28
Wulf et al.	2017 (Exp. 2)	labapplied	no	observe	y	adult	48	28
Wulf et al.	2017 (Exp. 2)	labapplied	no	two	y	adult	48	42
Wulf et al.	2005	applied	no	observe	y	adult	longer	26

Note. Setting = experimental setting; lab, applied, lab-applied. Comp = Compensation; yes, no, no mention. Choice = Choice-type; KR, KP, concurrent feedback, observational practice, incidental (instructionally-irrelevant), assistive device, practice schedule, task difficulty, amount of practice, two = collapsed groups. Pub = publication status; y = yes, n = no. Subpop = subpopulation; adult, children/adolescents, older adult, clinical populations. Interval = retention interval; 24-hours, 48-hours, longer than 48-hours.

6.3.4 Screening for outliers*:* The meta-analysis package ‘metafor’ (Viechtbauer, 2010; 2019) in R was used to screen the data for potentially influential outliers (see analysis script in Appendix B). In order to identify outlier values and exclude them from further analyses, the following nine influence statistics were calculated: a) externally standardized residuals, b) DFFITS values, c) Cook's distances, d) covariance ratios, e) DFBETAS values, f) the estimates of t^2 squared when each study is removed in turn, g) the test statistics for (residual) heterogeneity when each study is removed in turn, h) the diagonal elements of the hat matrix, and i) the weights (in %) given to the observed outcomes during the model fitting. Any experiment with effects identified as extremely influential by any three of the influence metrics were removed from subsequent analyses.

6.4 Pre-specified analyses

6.4.1 Random effects model: A naïve random effects model was fit to the retention effect sizes to estimate the average reported effect of self-controlled learning and to assess heterogeneity in effect sizes between experiments. Heterogeneity was evaluated with the *Q* statistic and described with I^2. A mixed-effects model was fit to evaluate whether differences in experimental design or sample characteristics moderated the effect of self-controlled learning.

6.4.2 Moderator analyses: The following six moderators were analysed separately in mixed-effects models: a) *Choice-type*: Choices were categorized as either instructionally-irrelevant, KR, KP, concurrent feedback, amount of practice, use of assistive device, practice schedule, observational practice, or difficulty of practice. b) *Experimental setting*: Experiments were categorized as either laboratory, applied, or laboratory-applied. We defined a laboratory setting as one where learners are asked to acquire a skill not typically performed in everyday life. We defined an applied setting as one where learners are asked to acquire a skill often performed outside of a laboratory. Finally, we defined a laboratory-applied setting as one where learners are asked to acquire a skill resembling skills often performed outside the laboratory but with researcher-contrived differences. c) *Subpopulation*: The following subgroups were analyzed: Adult (18-50 years of age), children/adolescents (under 18-years old), older adult (over 50-years-old), and clinical (clinical population defined by the research article). d) *Publication status:* Articles were classified as published or unpublished (theses). e) *Compensation*: Whether participants were compensated for participating in the experiment was categorized as compensated, not compensated, or not mentioned. f) *Retention delay-interval*: Coded as 24-hour, 48-hour, and longer.

6.4.3 Adjusting for selection effects: Selection bias in the motor learning literature is likely caused by filtering based on the statistical significance of results (Lohse et al., 2016). To assess and adjust for selection effects, the *weightr* package in R was used to fit a Vevea-Hedges weight function model to the retention data (Coburn & Vevea, 2017; Vevea-Hedges, 1996). The weight-function model estimates the true average effect, heterogeneity, and the probability that a non-significant result is observed in the analysis. Selection effects are modelled by a step function that divides the effects into two bins at one-tailed p =.025, coinciding with a two-tailed p-value of .05. The probability of a non-significant effect appearing in the model is estimated relative to the probability of observing a study with a significant effect. The selection-adjusted model was compared to the naïve random effects model with a likelihood ratio test. Better fit from an adjusted model suggests selection bias in the literature.

The adjusted estimate from the weight-function model was pre-registered as the primary estimate of the true average effect in this meta-analysis. Please note that while the weight-function model attempts to estimate the true effect of self-controlled learning after correcting for selection biases, the estimated effect cannot be considered definitive. Nevertheless, the adjusted estimate is likely less biased than the naïve random effects estimate (Vevea & Hedges, 1996). The difference between the estimates can be informative about the potential impact of selection biases, with larger disparities between models suggesting greater selection effects.

6.4.4 p-curve analysis*:* To investigate the evidential value of the self-controlled learning literature, the significant positive results at retention reported in peer-reviewed journals were submitted to a *p*-curve analysis (Simonsohn et al., 2015; 2015). In order to be included in the analysis, articles needed to meet the following criteria: a) be a published article, b) state explicitly that self-controlled learning was expected to be more effective than yoked practice, c) report inferential statistics comparing a self-control group and a yoked group directly on a retention test, d) conclude that the self-control group performed significantly better than the yoked group. If the article included multiple dependent measures showing a significant effect, the dependent measure priority list was used to select the highest priority measure. If only one measure was reported as significant, that effect was included even if the experiment included higher priority measures that were null. This resulted in a slightly different sample of effects from the random effects and weight-function models.

The distribution of significant *p*-values is a function of the power of the experiments included in the analysis. If a *p*-curve included only type 1 errors, the expected distribution would be uniform. As the power of included experiments increases, so too does the amount of right skew in the *p*-curve, with smaller *p*-values appearing more frequently than large *p*-values. The p-curve analysis tests the null hypothesis that there is no evidentiary value by analyzing the amount of right skew in the distribution of p-values. Conversely, if researchers peek at their data and stop collecting when they reach statistical significance, a practice known as *p*-hacking, the distribution of significant *p*-values under the null is left skewed, with *p*-values near .05 occurring more frequently. Varying mixtures of true effect sizes and intensities of *p*-hacking produce varying shapes of *p*-curve, therefore the observed *p*-curve was compared to the distribution of p-values expected if the studies were conducted with 33% power. It is unlikely that researchers would continuously conduct experiments that fail > 66% of the time whilst studying the self-controlled learning phenomenon. Observing a *p*-curve significantly 'flatter' than would be expected with 33% power would suggest a lack of evidential value among the significant results (Simonsohn et al., 2014).

6.5 Sensitivity analyses

The primary analyses were followed up with several sensitivity analyses. Sensitivity analyses are used to evaluate the sensitivity of the results to the specific parameters chosen for the original analyses. The self-controlled learning literature, like many areas of behavioural research, was not produced exclusively by registered experiments with pre-specified analysis plans and 100% reporting frequency. The complexity of selection effects at various levels, including editorial decisions, author decisions, analysis decisions, and missing data, renders the accuracy of modelled effects impossible to estimate (Carter et al., 2019). Producing a range of estimates based on varying assumptions is intended to provide the reader with a broader picture of the uncertainty of the point estimates in the primary analyses.

Bias correction methods vary in their performance depending on the total amount of heterogeneity, the true average effect size, the amount of publication bias, and the intensity of *p*-hacking in the data (Carter et al., 2019). In order to determine which bias correction models perform well in the various plausible conditions for data in this meta-analysis, model performance checks were conducted using the shiny app developed by Carter and colleagues (2019; http://www.shinyapps.org/apps/metaExplorer/). Conditions simulated were as follows: Medium publications bias (significant results published at 100% frequency, non-significant published at 20% frequency, wrong direction effects published at 5% frequency), tau = 0, .2, *g* = 0, .2, .5, *k* = 60, good performance defined as a maximum of .1 upward or downward bias, and maximum mean absolute error of .1, also tested with maximum bias and error values of .15. With good performance defined by a maximum bias in either direction of .1 and maximum absolute error of .1, the weight function model and *p*-curve models provided coverage across all plausible conditions except the highest heterogeneity condition ($\tau = .4$). With good performance defined as a maximum bias and error of .15, the precision-effect with standard error (PEESE) method provided good performance in all conditions. Therefore, sensitivity analyses were conducted on effect size data via *p*-curve and PEESE methods.

6.5.1 Primary p-curve: A leave-one-out analysis of *p*-curve results was conducted to assess the extent to which the primary results depended on the inclusion of one or two extreme results.

Results that depend on the inclusion of one or two extreme results should not be considered robust.

6.6 Results

6.6.1 Removal of outliers: Two studies were flagged as significantly influential outliers by all nine influence metrics calculated during data screening: Lemos, Wulf, Lewthwaite, & Chiviacowsky, 2017, $g = 3.7$, and Marques, Thon, Espanhol, Tani, & Corrêa, 2017, $g = 3.95$. No other effect sizes were identified as outliers by any metric. Both outliers were removed from all subsequent analyses.

6.6.2 Naïve random effects model: The naïve random effects model estimated the average treatment effect of self-controlled practice ($k = 56$, $N = 2251$), $g = .43$, 95%CI: .31 - .55. However, there was significant variability in the average effect estimated across experiments, $Q(\text{df} = 55) = 111.97$, $p < .0001$, $\tau = .31$. It was estimated that 48.3% (I^2) of the total variability in effect sizes across experiments was due to true heterogeneity in the underlying effects measured.

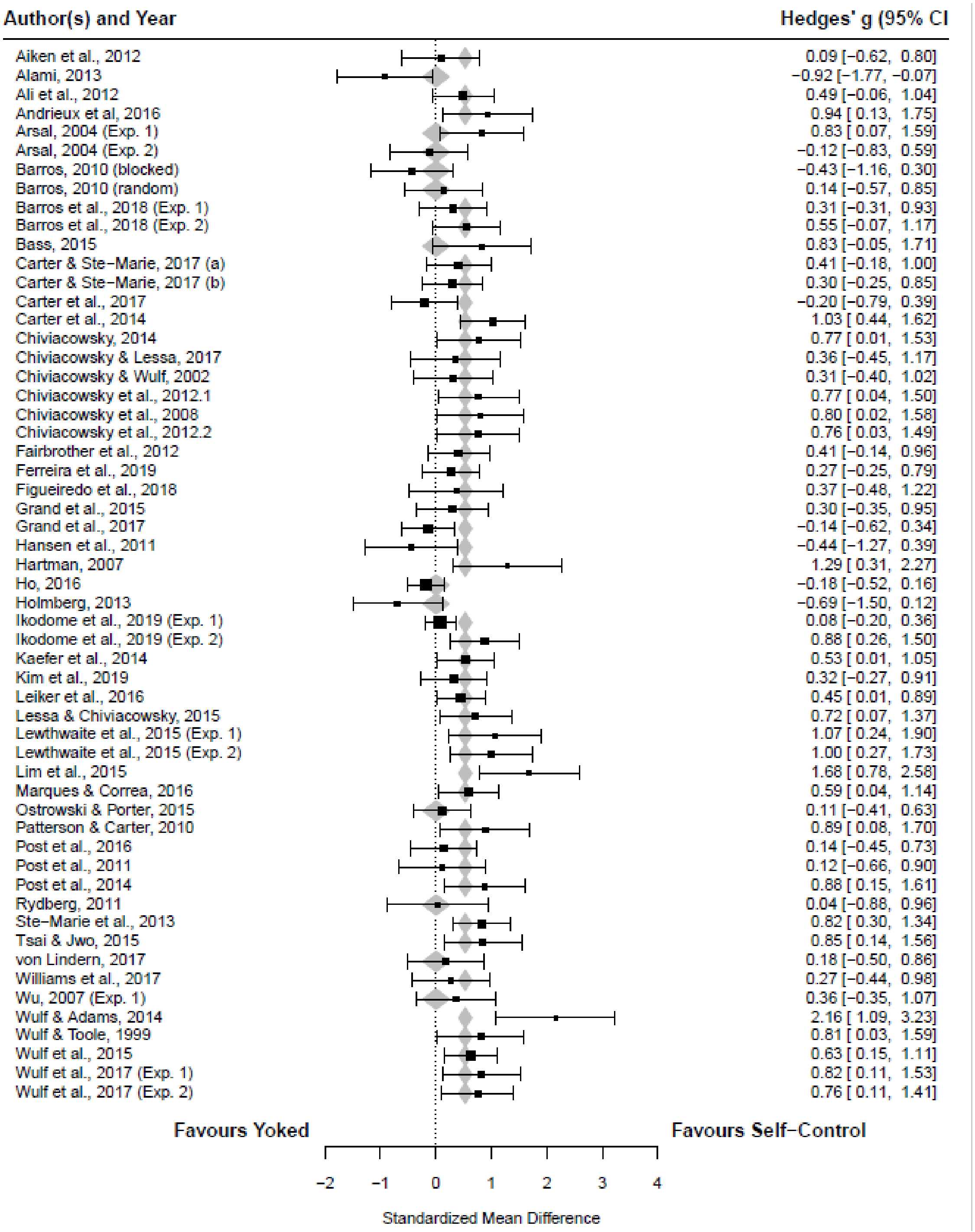

Figure 6.2. Forest plot of Hedges' *g* (95% CI) for self-controlled versus yoked groups on retention tests. Size of squares is proportional to $1/\sigma^2$ (precision). Light grey polygons represent unpublished (*g* = .004) and published (*g* = .53) 95% confidence intervals.

6.6.3 Moderator analyses: Six moderators selected for theoretical and/or methodological reasons were tested separately. Five moderators failed to account for a significant amount of heterogeneity: Experimental setting (p = .45, R^2 = .79%), compensation (p = .99, R^2 = 0%), choice-type (p = .762, R^2 = 0%), subpopulation (p = .73, R^2 = 0%), and retention interval (p = .54, R^2 = 0%). One moderator, publication status, accounted for a statistically significant amount of heterogeneity, p = .0001, R^2 = 42.57%. Among published experiments self-controlled practice had a strong benefit, g = .53, 95%CI: .41 -.65. However, among unpublished experiments self-controlled practice had essentially no effect, g = .004, 95%CI: -.23 -24.

6.6.4 Selection model: The weight-function model combines an effect size model and a selection model (Hedges & Vevea, 1996). The effect size model is equivalent to the naïve random effects model, specifying what the distribution of effect sizes would be in the absence of publication bias or other selection effects. The selection model accounts for the probability a given study survives selection based on its p-value and specifies how the effect size distribution is modified by selection. A weight-function model with a p-value cutpoint of (one-tailed) .025 was fit to the retention effect size estimates. The results of a likelihood ratio test suggest the adjusted model was a significantly better fit to the data than the unadjusted model, χ^2 (df = 1) = 17.24, p = .00003.[10] The adjusted effect size estimate was not significantly different from zero, g = .128, p = .20, 95%CI: -.069-.33. According to the adjusted model, non-significant results were 8% as likely to survive selection as significant results.

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[10] Be aware that the likelihood ratio test is not robust to misspecification of the random effects model (Hedges & Vevea, 1996).

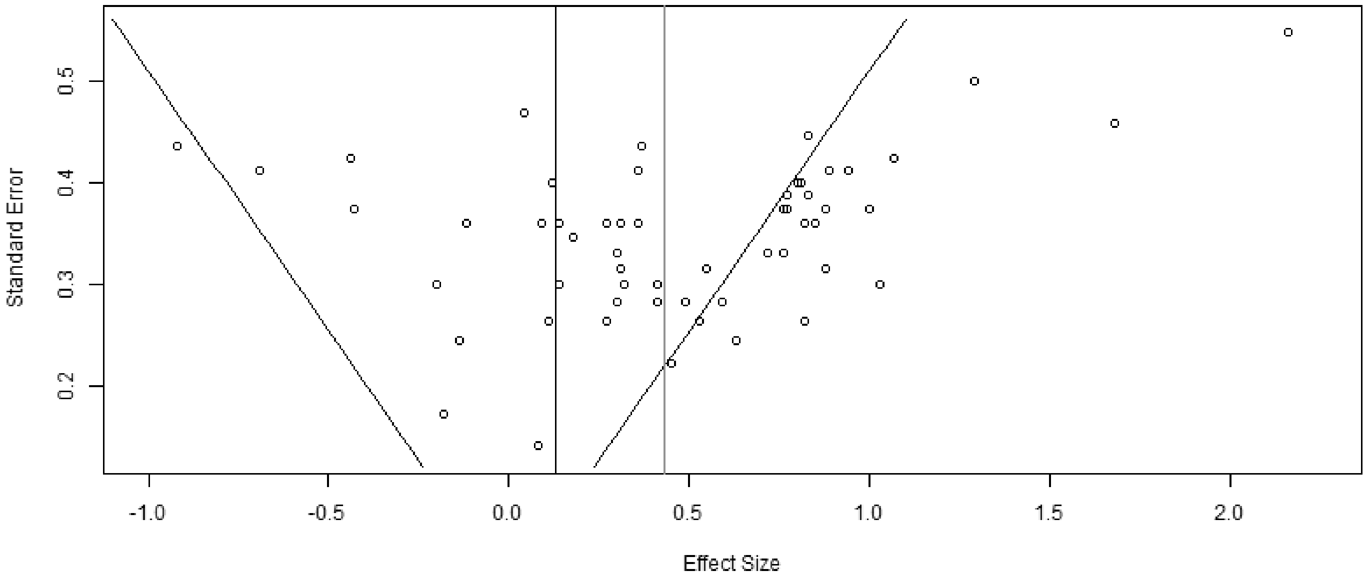
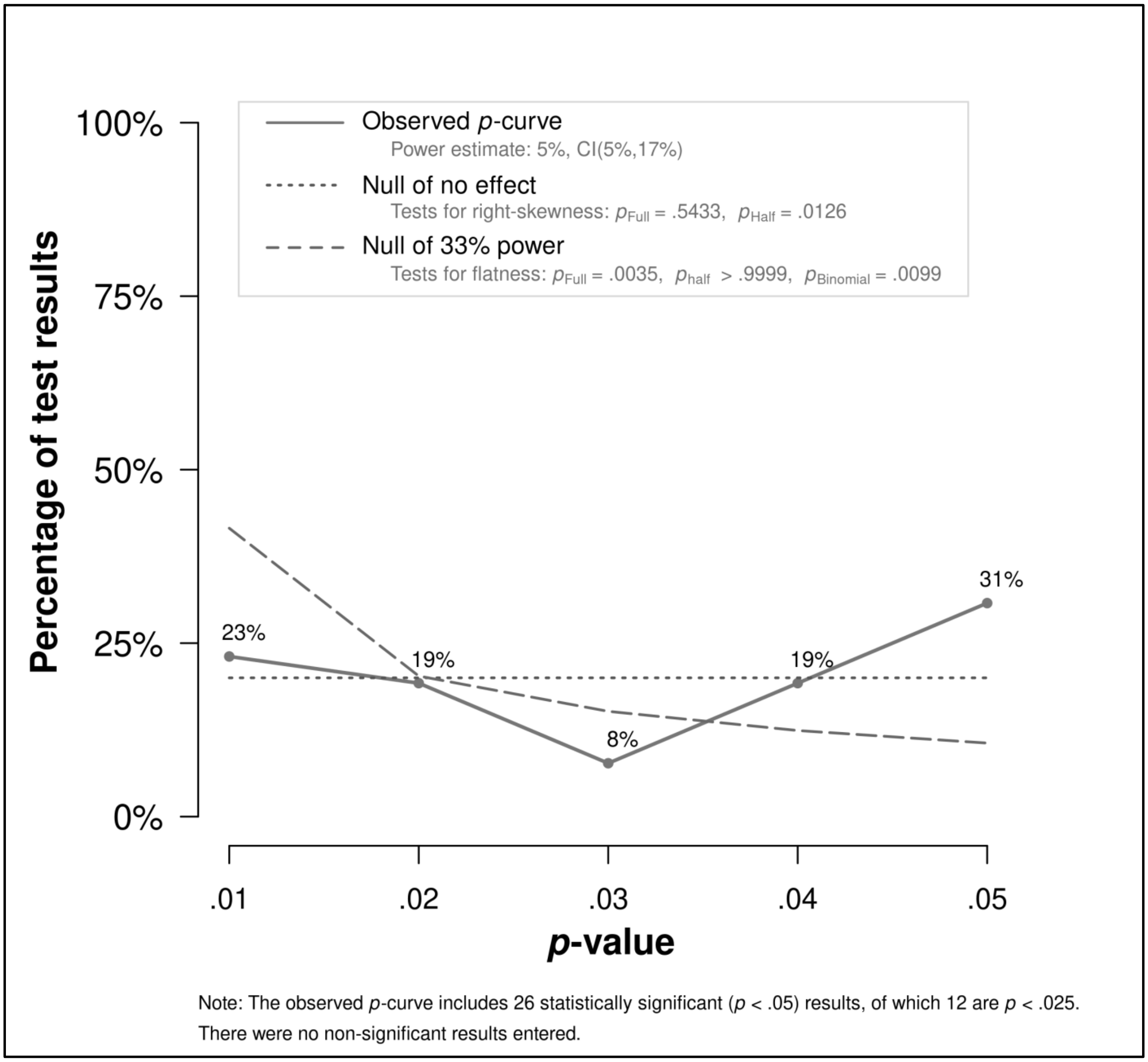


Figure 6.3. Funnel plot of self-controlled learning studies at retention. Standard error is plotted on the y-axis and Hedges' g is plotted on the x-axis. Light grey line represents naïve random effects model estimate (*g* = .43); vertical black line represents weight-function model adjusted estimate (*g* = .13); black contour lines represent two-tailed *p*-values of .05. In the absence of bias (and other forms of heterogeneity), the most precise experiments would centre on the naïve random effects estimate near the bottom of the plot and as experiments get progressively less precise they would move up the plot and spread out symmetrically. In the presence of bias, one would expect experiments to track to the right side of the positive contour line. The clustering of experiments just to the right of the positive contour line in the above plot suggests substantial bias.

6.6.5 p-curve: The purpose of the *p*-curve analysis was to investigate the evidential value in the published reports (*N* = 26) of statistically significant self-controlled learning benefits. Visual inspection of Figure 6.3 reveals a v-shaped distribution with the greatest frequency of *p*-values in the < .05 bin. A *p*-curve with this shape is only likely under conditions with low power and *p*-hacking. The observed *p*-curve was significantly flatter than would be expected if the experiments had 33% power, *p* = .0035, indicating an absence of evidential value. Conversely, the half *p*-curve (Simonsohn et al., 2015) was significantly right skewed, suggesting the presence of evidential value. Sensitivity analysis, however, revealed that the half curve does not remain significantly right skewed following removal of the most extreme *p*-value from the sample.



Note: The observed p-curve includes 26 statistically significant ($p < .05$) results, of which 12 are $p < .025$. There were no non-significant results entered.

Figure 6.4. *p*-curve analysis of published experiments that were statistically significant at retention. If the included experiments are studying a true null hypothesis the expected distribution of *p*-values is uniform, represented by the dotted line. If the experiments are studying a true effect, the expected distribution becomes increasingly right skewed as a function of statistical power. The expected right skewed distribution associated with 33% power is potted by the dashed line. The observed *p*-curve is plotted by the solid line and was substantially flatter than the 33% power distribution. The half *p*-curve analysis included *p*-values

below *p* = .025 and was significantly right skewed. The right skew did not survive deletion of the most extreme value.

6.6.6 Interim discussion. The primary results described above suggest that selection effects have caused a seriously distorted record of self-controlled learning. Estimated benefits are less than one third of the naïve estimate and not significantly different from zero: *g* = .128 (95%CI: -.069-.33). The *p*-curve analysis failed to detect robust evidence of a self-controlled learning effect. The performance of the weight-function model depends on the specific conditions present in the meta-analysis, although these conditions are unknowable (Carter et al, 2019). It was necessary to conduct sensitivity analyses with additional bias correction methods to assess the reliability of the selection-adjusted weight-function model estimate. Based on performance checks conducted under a range of plausible conditions, it was determined that sensitivity analyses conducted with a PEESE meta-regression and *p*-curve effect size estimation would provide good performance coverage across most plausible conditions.

6.7 Sensitivity analyses

6.7.1 PEESE model: When publication bias is present in a body of evidence, sample size and effect size can be negatively correlated (Stanley & Doucouliagos, 2014). The PEESE model fits a quadratic relationship between effect size and standard error to reflect the intuition that publication bias is stronger for low precision studies than high precision studies. The rationale is that low precision studies need to overestimate effects to achieve significance and get published, while high precision studies can publish without exaggerated effects, thus creating greater publication bias among lower precision studies (Carter et a., 2019; Stanley & Doucouliagos, 2014). A weighted-least-squares regression model was fit with effect size regressed on the square of the standard error, weighted by the inverse of the variance: $g_i = b_0 + b_1 se_i^2 + e_i$. The PEESE method estimated a non-significant benefit of self-controlled learning after controlling for publication bias: $g = .059$, $p = .625$.

6.7.2 p-curve error estimation: A *p*-curve model was fit to the overall retention effect size data, unlike the first primary *p*-curve which was fit to the reported significant results. The *p*-curve is a function of sample size and effect size, and since sample size is known, the effect size that provides the best fit to the observed *p*-curve can be estimated (Simonsohn, Nelson, & Simmons, 2014b). A *p*-curve analysis conducted with the *dmetar* package in R was used to estimate the average effect size among the statistically significant effects in the meta-analysis (Harrer, Cuijpers, Furukawa, & Ebert, 2019). The model estimated an average effect of $g = .159$.[11]

6.7.3 Acquisition and transfer: In light of the evidence that experiments are selected for positive self-controlled learning effects at retention, conducting pre-planned exploratory estimates of the effect of self-controlled practice on acquisition and transfer performance was deemed no longer appropriate. The primary take away from the analysis is that the reported self-controlled learning effects to date are unreliable.

6.8 Discussion

The primary objective of this meta-analysis was to assess the effect of providing choices during the acquisition of a motor skill on delayed retention performance in the general population. A secondary objective was to test between motivation and informational

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[11] The *p*-curve of effect sizes was significantly flatter than the expected 33% power curve as well, $p = .02$.

explanations for self-controlled learning benefits by investigating whether choice-type moderates the effect of choice. To this aim, an extensive search for experiments that compared self-controlled practice to a yoked comparison group was conducted. Effect size and moderator data were ascertained from data reported in the research articles or, in some cases, received directly from the authors of the studies. Efforts were taken to ensure that each effect size calculation and moderator code could be reproduced by an independent party. In parallel, the results of published experiments that achieved a hypothesized statistically significant result in favour of self-control were extracted directly from the articles and outlined in a *p*-curve discloser form. There pre-registered primary analyses were applied to the data and results were followed up with a suite of sensitivity analyses.

The naïve random effects model estimated a benefit from self-controlled practice of g = .43. However, the naïve model fails to account for selection effects, such as publication bias and *p*-hacking, and as such overestimates the true average effect when these selection effects are present (Carter et al., 2019; Stanley & Doucouliagos, 2014; Vevea & Hedges, 1996). Publication status was a significant moderator of the self-controlled practice effect, accounting for 42.6% of the total heterogeneity in the model. Published experiments reported an average benefit of g = .53 while unpublished experiments reported no benefit at all on average. It is possible that researchers use statistical significance, typically defined as $p < .05$ in a two-tailed test, to filter their results for publication. To account for potential selection effects driven by statistical significance, a weight-function model was fit to the retention test effect size data with a one-tailed *p*-value cutpoint of .025 included in the model (Vevea & Hedges, 1996). The adjusted model provided a significantly better fit to the data than the naïve random effects model. The model estimated the selection-adjusted benefit of self-controlled learning as *g* = .13, a dramatic departure from the naïve estimate of *g* = .43. Two additional bias correction techniques were conducted to assess the sensitivity of this result to changes in correction methodology. The PEESE method estimated the effect at *g* = .06, while *p*-curve estimated *g* = .16, and neither analysis was able to rule out the null hypothesis.

In parallel to the meta-analysis described above, a *p*-curve was conducted on the reported significant results. The *p*-curve used somewhat different inclusion criteria focusing only on published, statistically significant results suggesting a self-controlled learning benefit. In addition, the *p*-curve included results reported for any dependent measure in an article, even if the focal measure (of this meta-analysis) was reported as non-significant. Therefore, the *p*-curve was more inclusive of evidence reported by authors as favouring a self-controlled benefit while ignoring experiments with null effects. The results revealed both significant right skew below *p* = .025 (two-tailed) and a *p*-curve that was significantly flatter than a distribution with an expected power of 33%. The evidence of right skew, indicating superiority of self-control relative to yoked conditions, was tenuous and did not survive the deletion of the most extreme result – an experiment that reported a benefit from self-control of *g* = 2.16 (Wulf & Adams, 2014). The overall *p*-curve estimated the true power of the included experiments was 5% and rejected the hypothesis that the experiments contained evidential value.

It appears from these analyses that the substantial self-controlled learning literature is, as of now, insufficient to provide evidence that self-controlled practice is more effective than a yoked practice. The bias correction techniques applied in this analysis are sensitive to unknown conditions, such as the true average effect size and the amount of true heterogeneity, although efforts were taken to provide coverage across most plausible conditions. The corrected estimates produced by the weight-function model, *p*-curve, and PEESE methods appeared to converge on trivially small effects. Further, the *p*-curve of significant results suggested a lack of evidential value. Based on model performance parameters (Carter et al., 2019), point estimates of the self-controlled learning effect ranging from *g* = - .10 to .25 are plausible, with plausible upper confidence limits of *g* = .33. Thus, this analysis does not rule out the possibility that self-controlled practice provides meaningful motor learning benefits on average. The present literature, however, appears insufficient to establish that a self-control benefit indeed exists.

Turning to the current theoretical debates surrounding the motivational and informational underpinnings of self-controlled learning, these debates now seem moot, or at least premature. The effectiveness of self-control was not moderated by choice-type, suggesting that self-controlled practice may be ineffective regardless the nature of the choices provided. Indeed, the only factor we tested that moderated the effect of self-controlled practice was publication status.

6.8.1 Future studies

Given that the current meta-analysis failed to support the widely touted assertion of a substantial self-controlled learning benefit (Sanli et al., 2013; Ste-Marie et al., in press; Wulf & Lewthwaite, 2016), considerations need to be given to the design and research practices for future studies. Registered reports provide one possible path forward (Caldwell, Vigotsky, Nuckuls,... et al., 2018). A registered report involves submitting a research proposal to a two-phase peer-review. The first phase of the review occurs prior to data-collection and is assessed based on the proposed methodology, rationale, and potential contribution. If accepted in principle, researchers commit to carrying out the registered experiment and submitting the results in a final article for the second phase of peer-review. The final article is peer-reviewed for quality and adherence to the registered plan, but accept-reject decisions at this point are not based on the results. In theory, this practice should eliminate *p*-hacking and, for literatures composed entirely of registered reports, publication bias. A number of motor behaviour journals have begun adopting registered reports as an option for authors, including the *Journal of Sport and Exercise Psychology, Human Movement Science,* and *Frontiers in Movement Science and Sport Psychology.*

While registered reports are a potentially fruitful process to begin the accumulation of evidence regarding self-controlled learning, there are practical issues with investigating self-controlled learning that motor learning researchers may find overly burdensome. For example, in order to have 80% power to detect an effect of $g = .25$ with a two cell experimental design, 506 participants are required. If the weight-function adjusted estimate of $g = .13$ is accurate, $N = 1860$ are required. More challenging still would be testing between hypothesized motivational and informational mechanisms. For example, if a 2 (choice) X 2 (choice-relevance) experiment were conducted to test whether the instructional-relevance of choice fully attenuates its effect, four times as many participants would be required to maintain the same degree of power (Simonsohn, 2014). In contrast, the median sample size among experiments included in this meta-analysis was $N = 36$, which is typical of motor learning experiments in general (Lohse et al., 2016).

In addition to challenges with establishing that an effect exists, additional challenges will emerge if researchers were interested in generalizing the benefits of self-controlled practice beyond comparisons to a yoked group, as has been the case thus far (e.g., Ste-Marie et al., 2019; Wulf & Lewthwaite, 2016). As others have argued, yoking may allow for inferences to be made about the act of making certain choices, but it may not provide an adequate control group for evaluating best practices in an applied setting (e.g., Barros, Yantha, Carter, Hussein, & Ste-Marie, 2018; Ste-Marie, et al. in press; Yantha & Ste-Marie, 2019). Indeed, given that our estimate suggests the advantage of self-controlled over yoked practice is small, if it exists at all, it seems unlikely that self-control would be more effective than an instructor-guided practice. An instructor-guided group could easily be argued to have advantages over a yoked group, because of the ability for the instructor to adapt choices to the current practice context and to make use of personal experience and expertise. Following this logic, experiments investigating the benefit of self-controlled over instructor-guided practice could conceivably require substantially larger samples than experiments that use yoked comparison groups.

6.8.2 Exploratory analysis of pre-registered experiments

There have been, to our knowledge, three pre-registered experiments that have compared self-controlled and yoked practice (Grand et al., 2017; McKay & Ste-Marie, 2019; Yantha & Ste-Marie, 2019). Two of these experiments had failed to meet our inclusion criteria because they were not published or part of an accepted thesis at the time of the analysis (McKay & Ste-Marie, 2019; Yantha & Ste-Marie, 2019). Pre-registered experiments should provide unbiased estimates of the self-control effect and are therefore more useful for estimating the real average effect than attempting to correct biased experiments after the fact

(Carter et al., 2019). A random effects model was used to estimate the average effect of self-control in the three experiments and yielded *g* = -.02, 95%CI: -.25 - .20. These results converge with the bias-corrected estimates around trivially small differences between self-controlled and yoked practice conditions.

6.8.3 Conclusion

We set out to assess the effect of self-controlled practice on motor learning. The published literature on the subject to date appeared unambiguously supportive of a self-control benefit, yet the results of this meta-analysis suggest this may not be the case. If authors, reviewers, and editors select for statistical significance when deciding if experiments get published, the published literature becomes biased (Ioannidis, 2005). Worse still, filtering based on statistical significance may well incentivize researchers to leverage researcher degrees of freedom to achieve a significant result, a practice known as *p*-hacking, further biasing the literature (Wicherts, Veldkamp, Augusteijn, Bakker, van Aert, & van Assen, 2016). An instructive example of the potential impact of selection effects comes from research studying the so-called ego-depletion effect (Baumeister & Vohs, 2007; Hagger, Wood, Stiff, & Chatzisarantis, 2010). In a typical study, participants are asked to engage in activities that supposedly drain a limited reservoir of willpower, termed ego-depletion, and are subsequently measured on a dependent measure requiring an additional exertion of self-control, such as a Stroop task. The typical finding is that performance suffers on the second task if ego-depletion occurs beforehand. A meta-analysis by Hagger and colleagues (Hagger et al., 2010) reported the average effect of ego- depleting interventions on will power dependent measures was *d* = .62. There was apparent consensus in the field that will power relied on a limited resource due to the ostensibly unambiguous evidence in support of the theory (Baumeister & Vohs, 2018). Nevertheless, when bias correction methods were applied in a meta-analysis of self-control literature, the adjusted estimates often did not differ significantly from zero (Carter, Kofler, Forster, & McCullough, 2015). Subsequently, a pre-registered, multi-lab replication project tested a sample of N = 2141 and reported that the ego-depletion effect was close to zero (Hagger, Chatzisarantis, Alberts… et al., 2016). Thus, a prominent psychological construct substantiated by a large corpus of peer-reviewed evidence was investigated using cutting edge meta-analytic techniques that corrected for selection bias and the result was a trivially small estimated effect – an estimate supported by a subsequent large scale pre-registered replication effort.

In stark parallel to the ego-depletion literature the findings of the current research suggest the self-controlled motor learning literature may be similarly biased. As motor learning researchers in the field move forward, they are faced with the question of whether this effect is worth the resources required to study it. Considering the best estimate for the effect size yielded here and the challenges with generalizing to practical settings, we suggest that researchers allocate their efforts elsewhere.

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6.7 Appendix A: *p*-curve disclosure form

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
Andrieux, Danna & Thon (2012)	"Thus, we hypothesized that a practice condition in which the learner could set the level of task difficulty would be more beneficial for learning than a condition in which this parameter was imposed."	Two cell	Difference in means	"A follow up analysis restricted to the first two blocks revealed a significant difference between groups, *F*(1, 36) = 4.85, *p* < .05, $\eta^{2}p$ = .12. Self-controlled learners were significantly more accurate (*M* AE = 12.73 mm, *SE* = 1.57) than their yoked counterparts (*M* AE = 18.1 mm, SE = 1.87) after a 24-hr rest."	*F*(1, 36) = 4.85	
Andrieux., Boutin, & Thon (2016)	"Two main reasons led us to expect that self-control of nominal task difficulty would enhance motor skill learning, and especially when introduced during early practice rather than during late practice."	Four cell (Full self-control, full yoked, self-control then yoked, yoked then self-control).	Difference in means	"Planned pairwise comparisons revealed that the self-control groups exhibited lower RMSE (SC + SC, SC + YO, and YO + SC groups) than their yoked group counterparts (YO + YO group), F(1, 44) = 14.02, p < .01."	F(1, 44) = 14.02	
Brydges, Carnahan, Safir & Dubrowski (2009)	"We hypothesised that participants with self-guided access to instruction would learn more than participants whose access to instruction was externally controlled."	2 (Control: self, yoked) X 2 (Goals: process, outcome)	Difference in means	"The self-process group performed better on the retention test than the control-process group (Fig. 1). This effect was significant for time taken (F[1,23] = 4.33, P < 0.05)."	F(1,23) = 4.33	
Chiviacowsky (2014)	"We hypothesized that participants of the self-controlled group would show superior motor learning than yoked participants"	Two cell	Difference in means	"The Self group outperformed the Yoked group. The group main effect was significant, t(26) = 2.08, p .04, d .78."	t(26) = 2.08	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
Chiviacowsky, Wulf, de Medeiros, Kaefer & Tani (2008)	"Therefore, the purpose of the present study was to examine whether the learning benefits of self-controlled KR would generalize to children."	Two cell	Difference in means	"The self-control group had higher accuracy scores than the yoked group. This difference was significant, *F*(1, 24) = 4.40, *p* < .05."	*F*(1, 24) = 4.40	
Chiviacowsky, Wulf, Lewthwaite, & Campos (2012)	"The potential benefits of self-controlled practice have yet to be examined in persons with PD… under the assumption that self-controlled practice would enhance the learning of the task…"	Two cell	Difference in means	"The self-control group was overall more effective than the yoked group. Time in balance was significantly longer for the self-control group, F(1, 26) = 4.25, p < .05.".	F(1, 26) = 4.25	
Chiviacowsky Wulf, Machado & Rydberg (2012)	"We predicted that self-controlled practice, in particular the ability to choose when to receive feedback, would result in more effective learning compared to a practice condition without this opportunity (yoked group)."	Two cell	Difference in means	"The day following practice, a retention test (without feedback) revealed lower AEs for the self-control group than the yoked group (see Figure 2, right). The group difference was significant, with *F* (1, 28)= 4.72, p<0.05, η2=.14."	*F* (1, 28)= 4.72	
Hartman (2007)	"The primary aim of this study was to test whether there would exist a learning advantage for a self-controlled group, as opposed to a yoked control group, for learning a dynamic balance task."	Two cell	Difference in means	"To assess the relatively permanent or learning effects of practice with or without a self-controlled use of a balance pole, both groups performed a retention test on Day 3. The group effect was significant, *F(1, 17)* = 8.29, p < .01, with the Self-control group outperforming the yoked group."	*F(1, 17)* = 8.29	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
Kaefer, Chiviacowsky, Meira Jr. & Tani (2014)	"…both self-controlled groups (introverts and extroverts) will achieve a level of activation that facilitates learning through the control of stimulation source (feedback) in comparison with the groups that do not have control over it."	2 (Control: self, yoked) X 2 (Personality: introvert, extrovert)	Difference in means	"The groups' main effects were detected on the factor "feedback type": Self-controlled groups performed better, F(1, 52) = 4.13, p < .05, compared with externally controlled groups"	F(1, 52) = 4.13	
Leiker, Bruzi, Miller, Nelson, Wegman & Lohse (2016)	"We hypothesized that participants in the self-controlled group would show superior learning (i.e., better performance on retention and transfer tests) compared to the yoked group."	Two cell	Difference in means	"Controlling for pre-pest, there was a significant main effect of group, *F*(1,57) = 4.51, *p* = 0.04, *ηp2* = 0.07, such that participants in the self-controlled group performed better on the post-test than participants in the yoked group."	*F*(1,57) = 4.51	
Lemos, Wulf, Lewthwaite & Chiviacowsky (2017)	"Independent of which factor the learner is given control over e or whether or not this factor is directly related to the task to be learned e the learning benefits appear to be very robust."	Two cell	Difference in means	"On the retention test, choice participants clearly outperformed the control group. The group main effect was significant, F (1, 22) = 88.16, p < 0.01."	F (1, 22) = 88.16	
Lessa & Chiviacowsky (2015)	"it was hypothesized that older adult participants of the self-group would demonstrate superior motor learning results, presenting faster task times on the speed cup-stacking task, when compared with participants in the yoked control group."	Two cell	Difference in means	"The analysis of the retention test revealed significant differences between groups, F(1,34) = 4.87, p < .05… with participants of the self-control group presenting faster task times compared to yoked participants."	F(1,34) = 4.87	
Lewthwaite, Chiviacowsky, Drews & Wulf (2015; Exp. 1)	"In the present experiment, the choice learners were given was not related to task performance per se. Therefore, any learning benefits resulting from having, as opposed to not having, a choice would suggest that motivational factors are responsible for those	Two cell	Difference in means	"On the retention test, during which white golf balls were used, the choice group showed significantly higher putting accuracy (36.8) than the yoked group (26.4), F(1, 22) = 7.31, p < .05"	F(1, 22) = 7.31	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
	effects.”					
Lewthwaite, Chiviacowsky, Drews & Wulf (2015; Exp. 2)	“Given the potential theoretical importance of the finding in Experiment 1, we wanted to replicate it with another task and different type of choice.”	Two cell	Difference in means	“On the retention test 1 day later, the choice group demonstrated significantly longer times in balance than the yoked group, F(1, 27) = 7.93, p < .01.”	F(1, 27) = 7.93	
Lim, Ali, Kim, Choi & Radlo (2015)	“It was expected that a self-controlled feedback schedule would be more effective for the learning and performance of serial skills for both acquisition and retention phases than a yoked schedule.”	Two cell	Difference in means	“In the retention phase, there was a significant main effect for Group (*F (*1, 22) = 18.27, *p* < .05). The follow-up test indicated that the Self-controlled feedback group had higher performance (Cohen's *d* = 6.4) than the Yoked-feedback group during the retention test in both blocks.”	*F (*1, 22) = 18.27	
Patterson, Carter & Sanli (2011: comparison 1)	“We expected that the structure of this self-controlled practice context would either add to or compromise the existing benefits attributed to a self-controlled practice context.”	2 (Control: self, yoked) X 3 (Structure: full, all, faded)	Difference in means	“Specifically, the Self-Self condition demonstrated less |CE| compared to their Yoked-Yoked counterparts. This main effect was significant, *F*(1, 18) = 8.06, *p* < .05.”	*F*(1, 18) = 8.06	
Patterson, Carter & Sanli (2011: comparison 2)	“We expected that the structure of this self-controlled practice context would either add to or compromise the existing benefits attributed to a self-controlled practice context.”	2 (Control: self, yoked) X 3 (Structure: full, all, faded)	Difference in means	“The All-Self condition demonstrated less |CE| compared to the All-Yoked condition. This main effect was also statistically significant, *F*(1, 18) = 4.67, *p* < .05.”	*F*(1, 18) = 4.67	
Patterson, Carter & Sanli (2011: comparison 3)	“We expected that the structure of this self-controlled practice context would either add to or compromise the existing benefits attributed to a self-controlled practice context.”	2 (Control: self, yoked) X 3 (Structure: full, all, faded)	Difference in means	“The Faded-Self condition demonstrated less |CE| compared to the Faded-Yoked condition, supported by a main effect for group, *F*(1, 18) = 5.78, *p* < .05.”	*F*(1, 18) = 5.78	
Patterson, Carter	“We predicted the following: participants self-controlling their KR schedule would	2(KR Condition: self, yoked) X 2 (Schedule:	Difference in means	“The analysis revealed main effects of KR Condition, F(1,40) = 4.40, p < .05.”	F(1,40) = 4.40	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
& Hansen (2013)	demonstrate superior learning compared to those who do not engage in the increased processing demands used to individualize their KR schedule.”	random, blocked)				
Post, Fairbrother, Barros & Kulpa (2014)	“It was hypothesized that learners in the SC group would demonstrate superior accuracy and form scores compared with the yoked group during the retention test.”	Two cell	Difference in means	“The univariate ANOVA for retention revealed a significant group effect, $F(1, 29) = 6.08$, $p = .020$. The SC group had higher Accuracy scores the YK group”	$F(1, 29) = 6.08$	
Ste-Marie, Vertes, Law & Rymal (2013)	“We hypothesized that the Learner Controlled group would show superior physical performance of the trampoline skills… compared to the Experimenter Controlled group.”	Two cell	Difference in means	“A separate independent samples t-test showed that the Learner Controlled group had significantly higher performance scores compared to the Experimenter Controlled group at retention, $t(58) = 3.21$, $p < .05$, $d = .753$.”	$t(58) = 3.21$	
Wulf & Adams (2014)	“We asked whether giving performers an incidental choice would also result in more effective learning of exercise routines.”	2(Group: self-control, yoked) X 3 (Exercise: toe touch, head turn, ball pass) X 2 (Leg: left, right) mixed design with repeated measures on the final two factors.	Difference in means	“On the retention test… the choice group showed fewer errors than the control group. The main effects of group, F(1,18) = 25.35, p < .001, was significant.”	F(1,18) = 25.35	
Wulf & Toole (1999)	“If the beneficial effects of self-control found in previous studies are more general in nature (i.e., some general mechanism responsible for these effects), learning advantage would also be expected for self-controlled use of physical assistance.”	Two cell	Difference in means	“The main effect of Group, $F(1,24) = 4.54$, $p < .05$, was significant. Thus, allowing learners to select their own schedule of physical assistance during practice had a clearly beneficial effect on learning.”	$F(1,24) = 4.54$	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
Wulf, Clauss, Shea & Whitacre (2001)	“Importantly, however, if self-control promotes the development of a more efficient movement technique, one should see greater movement efficiency, as indicated by delayed force onsets, in self-control as compared to yoked participants.”	Two cell	Difference in means	Whereas the self-control group demonstrated relative force onsets that, on average, occurred about half the distance between the center of the apparatus and the participant’s maximum amplitude, the yoked group’s average force onset had already occurred after they had travelled less than 20% of the distance to the maximum amplitude. This group difference was significant, $F(1,24) = 4.43$, $p < .05$.”	$F(1,24) = 4.43$	
Wulf, Raupach & Pfeiffer (2005)	“Thus, if the learning advantages of self-controlled practice generalize to observational practice, allowing learners to decide when they want to view a model presentation should result in enhanced retention performance, with regard to movement form and, perhaps, movement accuracy, compared to that of yoked learners.”	Two cell	Difference in means	“Overall, the self-control group had higher form scores than the yoked group throughout retention. The main effect of group $F(1,23) = 5.16$, $p < .05$, was significant.”	$F(1,23) = 5.16$	
Wulf, Iwatsuki, Machin, Kellogg, Copeland, & Lewthwaite (2017) Exp 1.	“The purpose of the present experiments was threefold. First, we deemed it important to provide further evidence for the impact of incidental choices on motor skill learning. Given that self-controlled practice benefits for learning have frequently been interpreted from an information-processing perspective (e.g., Carter, Carlson, & Ste-Marie, 2014; Carter & Ste-Marie, 2016), with limited regard for rewarding-motivational explanations, further experimental evidence for learning enhancements through choices not directly	Two cell	Difference in means	“On the retention test one day later, the choice group demonstrated higher scores than did the control group. The group effect was significant, $F(1, 29) = 5.72$, $p < .05$.”	$F(1, 29) = 5.72$	

Original Paper	Quoted text from original paper indicating predicted benefit of self-control relative to yoked practice.	Study Design	Key statistical result	Quoted text from original paper with statistical results	Results	Robustness results
	related to the task seemed desirable (Experiments 1 and 2).”					
Wulf, Chiviacowsky & Drews (2015)	“To summarize, we hypothesized that an external focus and autonomy support would have additive benefits for motor learning (i.e., retention and transfer performance), as evidenced by main effects for each factor.”	2 (Autonomy support: self, yoked) X 2 (Focus: external, internal)	Difference in means	“On the retention test, the main effect of Autonomy Support was significant, *F*(1, 64) = 6.98, *p* < .01.”	*F*(1,64) = 6.98	
Ikodome, Kuo, Ogasa, Mori & Nakamoto (2019; Exp. 2)	“Previous studies manipulating participants’ choice of variables relevant to the experimental task have indicated that such choices have a positive effect on motor learning due to deeper information processing by the participants. Based on these studies, it is possible that this positive effect would be observed regardless of participants’ levels of intrinsic motivation, because this type of choice would not induce a change in perceived locus of causality from internal to external.”	2(Choice: self, yoked) X 2 (Motivation: high, low)	Difference in means	“An ANCOVA indicated significant main effects of choice, F(1, 39) = 8.93, p = .005.”	F(1, 39) = 8.93	

6.8 Appendix B: Analysis Script

```
# import datasets
data
N
# load the necessary libraries
library(metafor)
library(meta)
library(weightr)
library(dmetar)
# exclude subgroups that have been collapsed into single effect sizes
dat <- data[-c(16,17,20,21,87,88),]
# screen for influential cases
res <- rma(ret_g, ret_v, data = dat)
inf <- influence(res)
# view plots of influence diagnostics
plot(inf, dtfb = yes)
# identify influential cases
print (inf)
# remove influential cases
mydata <- dat[-c(52,58),]
# fit naive random effects model to retention data
rma(ret_g, ret_v, data = mydata)
# test if moderators account for significant amount of heterogeneity
# setting
rma(ret_g,ret,v, mods = ~factor(setting), data= mods)
# compensation
```

```
rma(ret_g,ret,v, mods = ~factor(comp), data= mods)
# subpopulation
rma(ret_g,ret,v, mods = ~factor(subpop), data= mods)
# retention interval
rma(ret_g,ret,v, mods = ~factor(interval), data= mods)
# publication status
rma(ret_g,ret,v, mods = ~factor(pub), data= mods)
# to test choice-type moderator exclude collapsed effects from data
mod_full <- data[-c(18,22,89),]
# remove influential cases
mods <- mod_full[-c(52,58),]
# choice-type
rma(ret_g,ret,v, mods = ~factor(choice), data= mods)
# fit weight-funtion model
x <- mydata$ret_g
v <- mydata$ret_v
weightfunc(x,v)
# sensitivity analyses
# fit PEESE meta-regression
peese <- lm(x~v, weights = 1/v)
summary (peese)
# estimate effect size with p-curve
ret <- metagen(ret_g, ret_se, data = mydata)
pcurve(ret, effect.estimation = TRUE, N = N)
```

7. Chapter 7

Elaborated Discussion of Article 3

In this elaborated discussion, some features of the meta-analysis that could have been conducted differently are discussed and their impact on the results is explored. The search procedure, inclusion criteria, and dependant variable selection are discussed in turn, followed by a characterization of the missing data. In addition, supplementary and exploratory analyses of the acquisition and transfer data are reported. Finally, the implications of this meta-analysis for OPTIMAL theory are discussed.

7.1 Search procedure

The search strategy employed in the meta-analysis sought to acquire a comprehensive record of self-controlled learning experiments as efficiently as possible. Motor learning experiments are listed in several databases, but none contain a comprehensive inventory of self-controlled learning experiments. Google Scholar is the exception but returns an unwieldy number of hits. Therefore, while a fixed search strategy was initially employed, each researcher also leveraged their own expertise to track down as many articles that potentially met our inclusion criteria as possible. The result, we think, is a thorough record of the self-controlled learning literature, although no individual database was comprehensively searched. As with any search strategy, it is possible we missed eligible experiments. However, if one considers the type of missing experiment that could substantively change our findings, that is, a highly precise experiment with a strong self-controlled learning effect, it would seem likely such an experiment would have a high profile and be relatively easy to find. Therefore, it seems unlikely that any experiments were missed that would significantly alter our main results.

7.2 Inclusion criteria

As a reminder, randomized experiments were subject to five criteria for inclusion in the meta-analysis: 1) A self-control group in which participants were asked to make at least one choice during practice, 2) a yoked-group that experienced the same practice conditions as the self-controlled group, 3) a delayed ~24-hour retention test or test with longer delay interval, 4) an objective measurement of motor performance, and 5) publication in a peer-reviewed journal or acceptance as part of a Master's or PhD thesis. In this section, the implications of these criteria on the overall results of the meta-analysis are discussed.

The focus of the meta-analysis was on motor learning. Kantak and Winstein (2012) highlighted the tendency for practice variables to have different effects on the day of acquisition relative to delayed retention tests, a phenomenon they refer to as the performance-learning distinction. As such, inclusion criteria were selected that required experiments to report a delayed retention test. Requiring a retention test excludes more powerful-within subject designs that may provide stronger evidence for a self-controlled practice effect on performance. If such evidence exists, it is for transient performance effects which are potentially different from effects on motor learning (Kantak & Winstein, 2012). This meta-analysis is limited to drawing inferences about learning effects.

The inclusion criteria also required experiments to have been published or part of accepted theses. The logic was that these written works would have undergone peer-review, and thus, could be considered to be high quality experiments. More data in a meta-analysis does not necessarily improve its quality; in fact including lower quality data is said to degrade, rather than improve, the accuracy of the estimates (Stanley, Jarrell, & Doucouliagos, 2010). Nevertheless, it is noted that unpublished experiments that were not theses were not sought out and they may contain unbiased estimates of the self-controlled learning effect. Without searching conference proceedings for unpublished abstracts, we cannot know how many unpublished experiments have been excluded from this analysis. Given the nature of our primary findings, however, it seems unlikely that the excluded unpublished literature would provide evidence for a self-controlled benefit that is missing from that of the published record.

7.3 Dependent variable selection

Many of the self-controlled learning experiments analyzed in this study included multiple dependent measures. However, including multiple measures from the same experiment introduces bias and inflates the variance of the mean estimate (Scammacca, Roberts, & Stuebing, 2014). Although there are a variety of methods for dealing with multiple measures from the same studies in meta-analysis, we chose to create a priority list and always select the highest priority dependent measure that was reported. If the highest priority measure was not described in adequate detail to calculate the effect size but a lower priority variable was, the authors were contacted and the data were requested. If the authors could not provide the data for the highest priority dependent measure reported in their study, the experiment was left out of our analysis. Alternatively, we could have averaged across dependant measures or chosen the focal dependent measure, if reported, in each study. Next, the potential benefits of our priority-list approach are described. Nevertheless, this dependent measure selection strategy also had drawbacks. Most notably, data were ignored and several experiments were excluded from analysis that would have been included with other strategies. Our selection strategy, therefore, had its own selection effects.

The rationale for selecting the approach we did was based on five considerations. First, our interest was in motor learning as reflected by an enhanced capability to perform a skill. Motor learning studies often report multiple error measures but they are not equally coupled with performance outcome. Constant error, for example, was not included on the priority list because it is possible to have zero constant error while performing terribly overall. Therefore, we chose to prioritize measures that could be considered to be tightly coupled with performance, like AE, RMSE, and ACE. If these measures were not used, measures that are only correlated with performance, such as variable error, movement time, and movement form, were selected. We reasoned this selection strategy would focus the analysis on measures related to improved skill while deemphasizing other effects. Second, we reasoned that averaging across dependent measures could introduce additional heterogeneity to the analysis by including potentially disparate dependent measures. The third, fourth, and fifth considerations all relate to avoiding bias but differ with regard to the source of the bias and the alternate method that would include such bias. Thus, the third consideration was that imposing a priority list was thought to better avoid biases that could emerge from selecting the most focal measure in a given study, because an unknowable percentage of studies may have defined the focal measure based on the strength of the findings. Fourth, we reasoned that some measures may only get reported if they support the predicted benefit of self-control. Scammacca and colleagues (2014) reported that effect size estimates were inflated when random dependent measures were selected in a meta-analysis case study, perhaps reflecting a selective reporting bias. Averaging across all reported measures - a fair alternative to our approach - could conceivably pick up some of this reporting bias. Fifth, we ignored lower priority measures with data when higher priority measures lacked data because we reasoned there could be a systematic reason for this pattern: preference for reporting data associated with positive effects. Indeed, there were articles where the only measure reported with sufficient data to calculate an effect size was also the only measure with a significant result (e.g., Wulf, Raupach, & Pfeiffer, 2005). Next, the missing data are reviewed to provide a qualitative understanding of what was missed by not including articles with missing data.

7.4 Missing data

Of the 79 experiments that met the eligibility criteria of this meta-analysis, 23 were excluded because of missing data. Those 23 experiments include 13 experiments that reported a statistically significant result. The high frequency of significant results among the missing data is evidence our own selection procedures were not the cause of the selection effects observed in the meta-analysis. Among the 13 experiments with missing data reporting a significant self-control benefit, one reported an inappropriate analysis (Hemayattalab , Arabameri, E., Pourazar, & Ardakani, 2013)[12], one reported statistics that do not match the experimental design (Jalavand, Bahram, Daneshfar, & Arsham, 2019)[13], one reported significant effects on a partial analysis of their data rather than overall (Brydges, Carnahan, Safir, & Dubrowski, 2009), and one was identified by Lohse and colleagues (2016) previously as an outlier study (Carter &

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[12] Although data were collected in one dimension using concentric circles, AE and a measure of dispersion were analyzed together in a MANOVA. This measure of dispersion is not an accurate reflection of variability on a two-dimensional task for reasons described by Hancock and colleagues (Hancock, Butler, & Fischman, 1995).

[13] A subgroup analysis involving two groups $n = 15$ was reported with $df = 56$. The article reports r^2 effect sizes associated with each test that cannot be reproduced with the reported statistics or best guesses.

Patterson, 2012). The meta-analysis may have been strengthened by the exclusion of these results (Stanley et al., 2010).

Among the remaining nine experiments reporting a significant effect with missing data, two reported effects collapsed across immediate and delayed retention only (Patterson, Carter, & Hansen, 2013; Wu & Magill, 2011), two reported null effects on a higher priority measure and did not include sufficient data to calculate the effect size, while reporting a significant effect on a lower priority experiment (Wulf, Clauss, Shea, & Whitacre, 2001; Wulf, et al., 2005; both studies were included in the primary *p*-curve analysis), and five compared three or more groups in an omnibus ANOVA and reported the group effect as significant but did not include sufficient data to calculate the effect size for the self-control versus yoked comparison (Chen, Hendrick, & Lidor, 2002; Ghorbani, 2019; Huet et al., 2009; Janelle et al, 1997; Norouzi, Hossini, & Aghdasi, 2015). There were 10 more experiments with missing data that failed to find a significant self-controlled learning effect. The primary results of this meta-analysis suggest that precise, pre-registered experiments observing a self-controlled benefit would be required to establish an evidentiary basis for the purported effect. No such experiment was excluded by our selection procedures.

7.5 Acquisition and transfer

Although retention results were the primary focus of this meta-analysis, we also endeavoured to ascertain acquisition and transfer effects when they were reported. Given the evidence of substantial selection based on significant retention results, we expected the acquisition and transfer effects to be biased. However, we do not expect that researchers simultaneously select based on multiple time points, so it seemed less likely that a weight-function model would adequately account for selection effects at the acquisition and transfer time points. Here we present an exploratory analysis of the acquisition and transfer data to evaluate our intuition.

First, to describe the average effect reported in the literature, separate naïve random effects models were fit to the acquisition and transfer effects. The average effect at acquisition was $g = .39$, 95%CI: .24-.53. The test for heterogeneity was significant, Q (df =35) = 61.85, p = .003, $\tau = .29$. The average effect at transfer was $g = .47$, 95%CI: .26 - .68. There was substantial total heterogeneity in the transfer data, $Q(df = 31) = 94.81$, $p < .0001$, $\tau = .50$. The average benefit of self-control was relatively stable across time points: .39, .43, .47.

Next, separate weight-function models with a $p = .025$ (one-tailed) cutpoint were fit to the acquisition and transfer results. The adjusted estimate for the acquisition effect was $g = .21$ and for the transfer effect was $g = .20$. The weight-function models both provided barely significant improvement in fit relative to the naïve effects models ($p = .0335$, $p = .0337$). Although it was expected that the weight-function model would not fit the acquisition and transfer results as well as the retention results, the substantial corrections applied to the adjusted estimates were surprising. Perhaps there is a shadow of the retention-based selection effects in the correlated acquisition and transfer data that is captured by the weight-function model, resulting in similar intercepts but a poorer fit.

7.6 Implications for OPTIMAL theory

The underling mechanisms of self-controlled learning are of central relevance to OPTIMAL theory (Wulf & Lewthwaite, 2016). Most, but not all, of the evidence that autonomy support enhances motor learning comes from the self-controlled learning literature. Nevertheless, Wulf and colleagues (Wulf, Iwatsuki, Machin, Kellogg, Copeland, & Lewthwaite, 2017) have argued that autonomy support explains self-controlled learning effects in general. A key prediction of OPTIMAL theory was supported by this meta-analysis: choice-type was not a significant moderator of self-controlled learning. Experiments that provided self-control of an instructionally-irrelevant feature of practice reported effects as large as or larger than the typical self-controlled learning experiment. However, the primary finding of this meta-analysis is that the benefit of self-controlled practice in general is small to negligible. As such, most of the evidence that autonomy support enhances motor learning is in question. This topic is taken up further the General Discussion.

8. Chapter 8

General Discussion

8.1 Overview of purpose

The purpose of this dissertation was to test and potentially extend OPTIMAL theory. The authors of OPTIMAL recommend asking learners to choose their feedback and practice schedule in order to satisfy their need for autonomy, but that leaves open the opportunity for learners to choose schedules that guidance and schema theory predict are suboptimal. What if a learner chooses a poor schedule? According to OPTIMAL theory the effect of making choices is independent of the content of those choices. Therefore, it was possible to manipulate choice and schedule independently and test OPTIMAL against guidance and schema predictions. By testing OPTIMAL theory against guidance and schema, it was hoped that one of two outcomes would be achieved: a) OPTIMAL theory is successful and has passed what can be described as a severe test, that is, one that a theory would likely have failed if it were not true (Mayo, 2018), or b) One or both of the competing theories are successful and OPTIMAL theory can be improved by incorporating optimal feedback and practice scheduling into the optimal practice scenario. Both scenarios would have represented a step forward for the field, either by increasing confidence in the OPTIMAL model or by discovering its limits and offering improvements. However, a third scenario emerged and focused the final study of this dissertation on determining whether autonomy support produces a noticeable benefit for motor learning at all.

8.2 Summary of findings

In Experiment 1, a 2 (autonomy support: choice, yoked) X 2 (KR schedule: 100%, 50%-faded) factorial design was employed to test the independent and combined effects of autonomy support and KR schedule on expectancies, motor learning and performance. This design allowed us to test, conditional on the OPTIMAL theory claim that the effect of choice is independent of the content of the choice, what happens if the learner chooses a theoretically good versus poor feedback schedule. According to the guidance hypothesis, 100% feedback enhances performance but degrades motor learning. Conversely, OPTIMAL theory suggests that feedback schedule will not be important if the learner is asked to make choices during practice. The results were more consistent with OPTIMAL theory than the guidance hypothesis. Although there were no statistically significant effects observed for either independent variable, the results were directionally inconsistent with the guidance hypothesis. The 100%-KR group putted somewhat more accurately in acquisition and post-testing, rather than displaying a reversal interaction as predicted by the guidance hypothesis. The autonomy support groups had slightly more accurate putting scores than the yoked groups in both acquisition and post-testing and had somewhat higher reported expectancies. These null results came despite a final sample size of 72, more than twice the median sample size in the self-controlled learning literature. The observed effect of autonomy support on motor behaviour was trivially small: 10% of a standard deviation.

In Experiment 2, the statistical power was increased, now providing 80% power to detect a 50% of a standard deviation effect. The experiment was four times the size of the median self-controlled learning experiment and provided the most precise estimate of the autonomy support effect to date. As planned, Experiment 2 crossed practice schedule (constant, variable) with autonomy support (choice, yoked), comparing the predictions of schema and OPTIMAL theories. Otherwise the logic was the same as in Experiment 1. The results were inconsistent with OPTIMAL theory: although the autonomy support group reported enhanced perceptions of autonomy need satisfaction, the yoked group performed significantly more accurately than the autonomy support group. In further discordance with OPTIMAL, although constant practice was beneficial to acquisition performance, it did not facilitate learning advantages, and this change in effectiveness was significant. Although not significant, the results were directionally consistent with schema theory. Finally, there was no significant difference between yoked and autonomy support groups on reported expectancies, though the yoked group reported higher expectancies on average.

Consecutive experiments failed to observe a significant benefit of autonomy support on motor learning, despite substantially more power than experiments that report an effect. Further, Experiment 2 observed results significantly discordant with the predicted benefits of autonomy support on motor performance. Similarly, there was no significant effect of feedback or practice schedule in either experiment. Lohse and colleagues (Lohse, Buchanan, & Miller, 2016) have sounded warnings that the motor learning literature is positively biased, underpowered, and *p*-hacked, which, taken together with the results of the first two experiments, raises the question of whether the reported benefits of choice are reliable. In order to evaluate the evidence that providing learners with choices during practice enhances their motor learning, Study 3 was a meta-analysis conducted on the self-controlled learning literature with bias correction methods applied to estimate and adjust for selection effects.

The results of Study 3 suggest that providing learners with choices during practice does not have a significant effect on motor learning. Although a naïve random effects model estimated the benefit of self-controlled learning as *g* = .43, publication status accounted for

40.5% of the heterogeneity in effects. Non-published experiments estimated the effect of self-controlled learning as less than 1% of a standard deviation, while published studies estimated the effect as $g = .53$. A weight function model including a .025 (one-tailed) *p*-value cutpoint provided a much better fit to the data and estimated the effect as $g = .13$ and not statistically different from zero. Multiple bias correction techniques were evaluated for performance in the plausible but unknowable conditions present in the self-controlled literature. The weight-function model, *p*-curve, and PEESE method were identified as providing good performance across most conditions. The *p*-curve estimated the effect of self-control as $g = .16$ and not statistically significant. The PEESE method estimated the effect as $g = .06$. A *p*-curve of the results reported as statistically significant revealed the most common *p*-values in the self-controlled learning literature are between .04 and .05, suggesting *p*-hacking was used to help underpowered studies produce significant results.

The results from Experiment 1 and Experiment 2 are consistent with the bias corrected estimates reported in Study 3. The totality of evidence in this dissertation suggests that, contrary to the central predictions of OPTIMAL theory, autonomy support does not have a meaningful effect on expectancies, motor performance, or motor learning. Instead, the appearance of robust effects in the literature may be an artifact of selection effects caused by filtering results based on statistical significance.

8.3 Implications

8.3.1 OPTIMAL theory: The implications of this dissertation are profound for OPTIMAL theory (Wulf & Lewthwaite, 2016). At present, it seems most likely that autonomy support has no meaningful effect on motor learning or performance and selection effects have caused the impression that it does. Therefore, this dissertation calls into question the veracity of the autonomy support predictions in OPTIMAL theory. The prediction that variables that enhance performance will also enhance learning was not supported in Experiment 2, where a significant interaction between practice performance and transfer performance was observed for practice schedule. The failure of this prediction calls into question the self-reinforcing virtuous and vicious cycles that are central to OPTIMAL theory's account of motor learning and performance.

In order for OPTIMAL theory to accommodate the issues raised by the present research, work will be required on both empirical and theoretical fronts. On the empirical front, multiple large scale (and registered) experiments will need to be conducted in order to determine if autonomy support has a non-zero effect on motor learning. The present research cannot rule out small but meaningful effects of autonomy support, but the extant literature is insufficient to establish whether such an effect exists. Importantly, future experiments will need to select appropriate autonomy support interventions that both satisfy the need for autonomy while also avoiding potential confounds. The experiments in this dissertation provided instructionally-irrelevant choices which did not offer the chooser any particular advantage during the learning or performance of the motor task. Most experiments in the self-controlled learning literature have provided instructionally-relevant choices, confounding potential autonomy support effects with other possible benefits, such as strategic scheduling or uncertainty reduction. Therefore, with respect to avoiding confounds, instructionally-irrelevant choices will continue to be the ideal choice for testing the autonomy predictions in OPTIMAL theory. Further, the specific instructionally-irrelevant choices provided in this dissertation had a noticeable impact on self-reported perceived autonomy support. Although OPTIMAL theory posits that all choices have similar effects regardless of content, it is crucial that the choices provided in future experiments work to support the learners’ need for autonomy.

On the theoretical front, OPTIMAL theory could advance more readily if a smallest effect size of interest were established within the theory. A smallest effect of interest would allow the core predictions of OPTIMAL theory to be falsified if the included variables really have a null effect, rather than only in the extreme circumstances where the true effect of the included variables is really the opposite of what has been predicted. Further, a smallest effect of interest would facilitate decisions with respect to adding new factors to the theory, restricting inclusion to only those variables that provide a meaningful advantage beyond the existing theory.

The use of autonomy support and expectancies in OPTIMAL theory appears to deviate from the native theories for these constructs, Self-Determination Theory (Deci & Ryan, 2000) and Social Learning Theory (Bandura, 1989), respectively. Although the cross-pollination of psychological theories may be a positive symptom of a cumulative science, respecting the jargon of individual theories is crucial for avoiding obfuscation and equivocation in theoretical arguments. OPTIMAL theory would benefit from a more detailed treatment of its factors with respect to their original definitions and underlying mechanisms.

The predicted relationship between performance and learning would benefit from further clarification than presently exists in OPTIMAL theory. In Experiment 2 in this dissertation, constant practice benefitted acquisition performance but did not benefit learning, consistent with the perspective advanced by Kantak and Winstein (2013). Indeed, when taken to its logical extreme, the prediction that conditions which enhance performance facilitate learning appears likely false on its face. Creating the least challenging practice condition possible would enhance performance relative to more challenging conditions, yet it seems unlikely this would lead to more effective learning. An improvement to this prediction would require that performance be enhanced *at a given level of difficulty*. The dopaminergic reward system is proposed to code for reward prediction error (Schultz, 2013) and difficulty of practice seems likely to influence reward prediction. While an unchallenging practice would produce high levels of relative performance, it would seem unlikely to produce high levels of reward prediction error since there would already be a high expectation for success. OPTIMAL theory presently highlights the importance of challenge by predicting that challenge enhances learning in the presence of prevailing success so it seems a logical to extend the importance of challenge to the prediction that enhancing performance facilitates learning. Notably, if OPTIMAL theory incorporated this suggestion, then the results in Experiment 2 in this dissertation would no longer be in contradiction to the OPTIMAL prediction, since constant and variable practice are not equally difficult.

8.3.2 Guidance hypothesis and schema theory: This dissertation was intended to test OPTIMAL theory and it was informative to use guidance and schema to carry out these tests. The results in Experiment 1 were inconsistent with the guidance hypothesis (Salmoni, Schmidt, & Walter

1984). Rather than being detrimental for motor learning, the 100%-KR condition was somewhat more effective than a reduced feedback schedule. Considering the primary findings of this dissertation, it seems fair to wonder how robust feedback frequency effects are. The guidance hypothesis inverted motor learning's understanding of KR frequency, contradicting a prior consensus that proposed higher frequencies of KR during practice result in superior motor learning (Bilodeau & Bilodeau, 1961). Perhaps the next breakthrough in the augmented feedback literature will result from adoption of open science principles, including pre-registration and high-powered experiments.

The results of Experiment 2 failed to confirm the schema theory prediction that variable practice leads to more effective transfer performance (Schmidt, 1975). However, results of Experiment 2 were directionally consistent with schema theory, suggesting the possibility that a type 2 error occurred. Perhaps an experiment with even more power may be required to detect the effect of variable practice while keeping type 1 error rates below 5%. A meta-analysis of the extant practice schedule literature could help calibrate future experiments and investigate potentially insidious selection effects.

8.3.3 Motor learning: Self-controlled learning is a prominent topic in the modern motor learning literature. The finding of this dissertation, that self-controlled learning may not have a meaningful effect, seemed unlikely *a priori* for two reasons. First, numerous authors have highlighted the ostensibly robust impact of providing choice during practice (Magill & Anderson, 2013; Sanli, Patterson, Bray, & Lee, 2012; Sigrist, Rauter, Riener, & Wolf, 2013; Wulf & Lewthwaite, 2016) and, to my knowledge, no authors have taken a position claiming that self-controlled learning, in general, is ineffective. Second, it is difficult to imagine a researcher predicting that a yoked condition would be more effective for motor learning, unless the yoking is done to the choices of a skilled scheduler (Hodges, Edwards, Luttin, & Bowcock, 2011). Despite these reasons to assume self-controlled learning is more effective than yoking, the results of this dissertation suggest that self-control of an instructionally-irrelevant variable (at least) is not meaningfully beneficial for motor learning. If self-controlled learning does have a real, positive effect, perhaps when providing instructionally-relevant choices, new high-powered and pre-registered experiments will be required to reliably detect such an effect. The extant literature is simply too biased to establish self-controlled practice is effective at this time.

Researchers have been discovering previously established phenomena are not reliable through a combination of bias correcting meta-analyses and high-powered, pre-registered experiments in various fields. For example, as discussed previously, a meta-analysis corrected for selection bias using the PEESE method in the 'ego-depletion' literature and estimated a null effect for ego-depleting interventions (Carter, Kofler, Forster, & McCullough, 2015), a result supported by large pre-registered replication efforts (Hagger, Chatzisarantis, Alberts… et al., 2016). Similarly, an accumulation of research had suggested that exposure to money related stimuli, called a money prime, can cause a self-sufficient orientation, leading to behavioural outcomes such as the desire to work alone and a decreased willingness to work with others (Vohs, Mead, & Goode, 2006). Yet, when meta-analysts corrected for bias using the weight-function model employed in Study 3, null effects were estimated for most subsets of money priming experiments (Lodder, Ong, Grasman, & Wicherts, 2019). As with ego-depletion, large scale pre-registered replication efforts reported null effects from money primes, consistent with the bias corrected estimates (Crawford, Fournier, & Ruscio, 2019). In a final example, research seemed to suggest that adopting expansive versus restrictive postures, known as power posing, could enhance testosterone levels and decrease cortisol levels (Carney, Cuddy, & Yap, 2010). The power posing literature was submitted to a *p*-curve analysis and the results suggested the effect of power posing was not statistically different from zero (Simmons & Simonshon, 2017). In line with the previous examples, large pre-registered replication attempts failed to observe benefits of power posing (Garrison, Tang, & Schmeichel, 2016). Perhaps it is less surprising in light of these findings that self-controlled learning may be a false positive that was selectively published into the appearance of a robust effect.

Considering the present zeitgeist, including the results of this dissertation, it is fair to question the reliability of other motor learning phenomena generally considered robust (Ioannidis, 2005). Additional reason for concern emanates from a recent meta-analysis that investigated recently published motor learning experiments (Lohse et al., 2016). The study reported a median sample size per cell of n = 11 in the sampled experiments. Samples this small would fail to detect obvious effects, that men weigh more than women, for example, three times out of four (d = .59, Simmons, Nelson, & Simonsohn, 2013). When experiments drop below 50% power, statistically significant effect size estimates become substantially exaggerated, called a Type M(magnitude) error (Gelman & Carlin, 2014). When an experiment is as underpowered as the typical motor learning experiment would be to detect the weight difference between men and women (25% power), statistically significant effects are expected to be exaggerated by 97% on average.[14] As power drops below 10%, the probability of a significant effect being in the wrong direction, called a Type S(sign) error, begins to increase rapidly. The primary *p*-curve analysis in Study 3 estimated the power of experiments reporting significant self-controlled learning effects approached 5%. The typical motor learning experiment would have power approaching 5% when investigating effects around 5% of a standard deviation. In this case, an observed statistically significant effect will be in the wrong direction roughly 38% of the time.

The results of this dissertation should raise a red flag for motor learning researchers. The sample sizes observed in the field are often too small to reliably detect plausible motor learning effects and it is unclear why the publication bias observed in the self-controlled learning literature would be specific to that line of research. Therefore, one may question the veracity of published significant findings, considering their likelihood in the absence of *p*-hacking and the propensity for Type M and Type S errors in underpowered research (Gelman & Carlin, 2014; Simmons et al., 2013). Large scale, registered replications may be required to determine which established motor learning effects are reliable and which are spurious (Caldwell et al., 2019; Ioannidis, 2005).

8.4 Strengths and Limitations

The first strength of this dissertation was its focus on research quality over quantity. Despite collecting as much data as five and half median sized motor learning experiments, only two experiments were conducted. This produced the two most precise estimates of the effect

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[14] The retrodesign() package in R facilitates this analysis. For example, an effect size that is 1.3 standard errors from the mean with an alpha of .05 and infinite degrees of freedom has a power of 25.5%. The expected Type M error is 1.9687 and the probability of a Type S error is .002.

of instructionally-irrelevant self-control observed to date, with assurances that researcher degrees of freedom were not available to bias the results (Wicherts, Veldkamp, Augusteijn, Bakker, Van Aert, Van Assen, 2016). These results, combined with the bias-corrected meta-analysis reported in Study 3, allowed for a confident rejection of the OPTIMAL theory hypotheses predicting (meaningful)[15] motor learning and performance benefits from autonomy support.

Relatedly, a second strength of this dissertation was the extensive effort taken to ensure the reproducibility of the meta-analysis. A recent investigation of meta-analyses suggests that many meta-analyses cannot be independently reproduced (Lakens, van Assen, Anvari… et al., 2017). Flexibility in inclusion criteria, dependent variable selection, and effect size calculation can make independent reproduction of analyses impossible. As such, independent corroboration of inclusion decisions, data extraction, and effect size calculation was required for each datum in the meta-analysis and *p*-curve analysis. Independent corroboration required detailed rules for each data extraction decision and these rules were pre-registered. Further, the data are openly accessible on the Open Science Framework and the analysis script is included in the appendix of the meta-analysis.

A third strength of this dissertation was the adherence to pre-planned analyses followed by the application of sensitivity analyses and tests of robustness to follow up significant findings. Two of the three studies in this dissertation were pre-registered in a publicly accessible depository (osf.io). Although Experiment 1 was not pre-registered in this way, the pre-specified analysis plan was followed strictly and the ethics application can demonstrate

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[15] Trivially small benefits in line with OPTIMAL predictions cannot be ruled out.

this. In Experiment 1, a robustness test involving collecting additional data changed a statistically significant result into a null result, preventing a false positive interpretation of the data. In Experiment 2 and Study 3, sensitivity analyses probed the possibility that the results of the primary analyses depended on the specific models specified in the analysis plan. In both cases, the sensitivity analyses supported the primary analyses, providing additional confidence in the main results.

A final strength of this dissertation was its combination of experimental and meta-analytic methods to probe the veracity of the OPTIMAL theory predictions motivating this research. While the experiments produced high powered and pre-specified replication failures, the meta-analysis provided a compelling explanation for these failures. As described in other fields, the combination of null bias-corrected meta-analytic estimates with pre-registered replication failures provides convincing evidence that the effect being investigated is not robust.

A limitation of this dissertation is its inability to reach a conclusive decision regarding the effect of self-controlled learning with instructionally-relevant choices. Although the meta-analysis suggests the effect of self-control is not moderated by choice –type, the evidence is too biased to reach definitive conclusions. At present, three high-powered and pre-specified experiments have failed to replicate the instructionally-irrelevant choice effect, each producing estimated effects more consistent with the bias corrected estimates in the meta-analysis than the naïve estimates (Grand, Daou, Lohse, & Miller, 2017; McKay & Ste-Marie, 2019a, 2019b). Conversely, one pre-registered experiment has tested the effect of an instructionally-relevant choice, and while failing to observe a significant effect, the observed effect was more similar to the naïve effects estimate than the bias corrected estimates (Yantha & Ste-Marie, 2019). Although the purpose of this dissertation was to test the autonomy predictions in OPTIMAL theory, a limitation of this work is that it is unable to completely address the possibility that certain self-controlled learning interventions result in meaningful benefits.

A second limitation of this dissertation is that it employed a single blind experimental design. Although double blinding a self-controlled learning experiment presents practical challenges, the potentially subtle effects of an instructionally-irrelevant choice may have been obfuscated by subtle and competing demand characteristics. Double blind experiments are not typically conducted in the motor learning literature because learners cannot be given placebos to maintain blinding during data collection. Future studies may address this limitation by using an automated data collection procedure.

A third limitation of this dissertation was that it focused on OPTIMAL theory at the expense of settling issues raised with the guidance hypothesis and schema theory. Generalizations from a single study are not typically warranted so this dissertation is ill suited to make inferences about feedback frequency or practice schedule (Amrhein, Trafimow, & Greenland, 2018). Nevertheless, the results from Experiments 1 and 2 provide precise and unbiased estimates of the learning effects of each variable, contributing to the accumulation of evidence in their respective literatures.

8.5 General conclusions

This dissertation provided a thorough test of the autonomy support predictions advanced in OPTIMAL theory. In consecutive experiments, providing instructionally-irrelevant choices during practice had little effect on motor learning. In Experiment 2, providing choices led to significantly less effective performance, despite evidence that choosing enhanced perceptions of autonomy satisfaction. A meta-analysis of experiments that provided learners with choices during practice and compared their motor learning to a yoked group suggested the putative benefit of self-controlled learning is possibly an artefact of selection biases. Taken together, these results provide convergent evidence that autonomy support may not meaningfully enhance motor learning or performance.

In addition, Experiment 2 provides evidence that variables can cause different effects on performance and learning measures, even when combined with autonomy support. In contrast, OPTIMAL theory predicts that variables have consistent effects on learning and performance. In light of these results, in addition to those reviewed by Kantak and Winstein (2012), the consistent effects prediction in OPTIMAL theory does not appear to be accurate.

The failures of OPTIMAL theory largely stem from a systemically biased motor learning literature (Lohse et al., 2016). Naïve estimates of self-controlled learning support OPTIMAL theory and reflect the qualitative understanding one would get from a thorough and meticulous review of the literature. The authors of OPTIMAL theory can be easily forgiven for following the available evidence because they were unaware of the evidence that was missing. One can only wonder how many other theories fit mechanisms to biases. A combination of publish or perish pressure and filtering for publication based on statistical significance may be undermining the trustworthiness of the motor learning literature and a serious rethinking of the existing incentive structures in academic research could be required to address these issues (Grimes, Bauch, & Ioannidis, 2018).

Moving forward, motor learning researchers in general and self-controlled learning researchers in particular can work to accumulate a reliable body of evidence in the following ways. First, pre-registering experimental protocols can eliminate the use of researcher degrees of freedom in confirmatory research and make explicit which degrees of freedom were used in exploratory research. Indeed, pre-registration is becoming the norm in psychology (Nosek & Lindsay, 2018). Second, increasing use of meta-analysis and bias-correction techniques can help determine which findings have a high probability of being true. These probable findings should then be tested in large scale projects with pre-defined equivalence bounds, based on the smallest effect size of interest, to allow for a definitive rejection of the null or the alternative hypothesis (Ioannidis, 2005; Lakens, 2017). In support of this goal, researchers may find it helpful to team up using a multi-lab approach (see Open Science Framework, 2015), adopt more efficient data-collection plans, such as sequential analysis (Lakens, 2014)[16], and submit registered reports, which, if accepted, help guarantee publication as long as the pre-specified plan is followed (Caldwell et al., 2019). Third, while acting as reviewers or editors, or when deciding whether to submit a research project for publication, researchers should be tolerant of

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[16] Sequential analysis adjusts the alpha to allow for multiple looks at the data while controlling the overall long run error rate. This procedure can reduce required sample sizes by 30% on average.

imperfect, unpredicted results. Instead, “underpowered studies with perfect results are the ones that should invite extra scrutiny” (Simmons et al., 2011, p. 1363).

The so-called replication crisis occurring in several disciplines has the potential to undermine public trust in research. Yet, according to a recent survey of the Europeans, faith in the research enterprise is maintained when individuals are told about reforms like those described above (Anvari & Lakens, 2019). Indeed, science has never guaranteed the right answer, merely a mechanism for self-correction. As a field, it is important that we continue to “fail forward.”

8.6 References

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9. Appendices

9.1 Appendix A: Demographic Questionnaire Experiment 1

Demographic Questionnaire	**Response**
Name:	
Sex:	
Age:	
1. Approximately how many times have you had a putting experience (e.g., mini putt or a round of golf).	
a. During last five years?	
b. During the last year?	
2. Have you had any experience being part of an organized sport in which you need to control an implement (e.g., hockey, soccer, tennis, etc.)? If so, please list all sports.	

9.2 Appendix B: Self-efficacy questionnaire Experiment 1

Please read the questions below and type your response in the RESPONSE column. There are no right or wrong answers. Consider the putting task and the coloured squares you have just seen. Use the scale below to indicate how many putts out of 10 you think can get in each of the squares listed on your next 10 putts. For example, if you believe you can putt 5 balls out of 10 in a given square (5/10), your response would be 5.

1/10, 2/10, 3/10, 4/10, 5/10, 6/10, 7/10, 8/10, 9/10, 10/10

QUESTIONS

How confident are you that you can putt balls into the area of the …	RESPONSE
1. green square (largest square, which also includes the yellow and red square area):	
2. yellow square (mid-sized square, which also includes the red square area):	
3. red square (smallest square):	

9.3 Appendix C: Basic Needs Satisfaction in Sport Scale (Ng, Lonsdale, & Hodge, 2011)

Please read the items below and type your response in the RESPONSE column. There are no right or wrong answers. Please answer as honestly as possible. Please respond to the following items using a 7-point scale:

1	2	3	4	5	6	7
Not true at all						Very true

QUESTIONS	RESPONSE
1. In this study, I get opportunities to make choices.	
2. In this study, I have a say in how things are done.	
3. In this study, I can take part in the decision-making process.	
4. In this study, I get opportunities to make decisions.	
5. In this study, I feel I am pursuing goals that are my own.	
6. In this study, I really have a sense of wanting to be there.	
7. In this study, I feel I am doing what I want to be doing.	
8. I feel I participate in this study willingly.	
9. In this study, I feel that I am being forced to do things that I don’t want to do.	
10. I choose to participate in this study according to my own free will.	

9.4 Appendix D: Self-Efficacy Questionnaire Experiment 2

Please read the questions below and type your response in the RESPONSE column. darts out of 9 you
There are no right or wrong answers. Consider the dart task you have just performed. Use the scale below to indicate how many darts out of 9 you think can get inside each of the circles listed on your next 9 throws For example, if you believe you can throw 4 darts out of 9 in a given circle (4/9), your response would be 4.

1/9, 2/9, 3/9, 4/9, 5/9, 6/9, 7/9, 8/9, 9/9

QUESTIONS

How confident are you that you can throw darts into the area of the …

1.Largest circle, including both smaller circles:

2. Middle circle, including the smallest circle:

3. Centre circle:

9.5 Appendix E: Ethics Approval

29/06/2018

Université d'Ottawa
Bureau d'éthique et d'intégrité de la recherche

University of Ottawa
Office of Research Ethics and Integrity

CERTIFICAT D'APPROBATION ÉTHIQUE | CERTIFICATE OF ETHICS APPROVAL

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Conditions spéciales ou commentaires / Special conditions or comments