BULL'S EYE-HAND COORDINATION:

VISUAL AND MOTOR CONTRIBUTIONS TO OBSERVATIONAL LEARNING

by

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A dissertation submitted to the Graduate School – Newark

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Graduate Program in Psychology

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Newark, New Jersey
May 2014

ABSTRACT OF THE DISSERTATION

Bull's Eye-Hand Coordination: Visual and Motor Contributions to Observational Learning

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Watching other people move affords observers many benefits such as presenting opportunities for social interactions, deciphering other's intentions and emotional states, and learning new motor skills. Observational motor learning is the process of learning to perform a novel motor skill by watching others execute that skill. Common coding theories of the visual and motor representations of actions allow for a relationship between action observation and action execution that makes observational motor learning possible. More specific theories related to observational learning conflict in terms of whether observed actions are first represented at the kinematic level or at the action goal level. The overarching goal of this series of experiments was to increase our understanding of how the visual system and the motor system work together to enhance action learning.

Experiments 1 and 2 examined the influence of model expertise on observational learning of dart throwing. Dart throwing was selected as the motor task of interest because it has been used previously in perception-action coupling research and because it represents an ecologically valid complex motor task. This differs from past research on action learning which has tended to rely on simple, contrived motor skills. In Experiments 1 and 2, participants threw darts before and after they watched an expert or a novice dart throwing model. To rule out the possibility that the observation of any dart throwing actions might improve an observer's ability to throw darts, Experiment 2 included an additional control condition involving a model playing basketball. No significant differences were found in participants' dart throwing abilities after the observation of either dart thrower or the basketball player. Instead, physical practice effects were sufficient

to account for all improvements in dart throwing performance.

Experiments 3 and 4 used measures of visual sensitivity, rather than motor performance, to assess the motor system's contributions to visual learning of other people's actions. Action observation is thought to involve an action simulation process that impacts an observer's ability to predict the outcomes of other people's actions. Thus, if an observer's motor system is otherwise engaged, that observer should be compromised in his or her ability to simulate another person's actions and as a result, should demonstrate deficits in predicting action outcomes. In Experiment 3, participants completed a dart throwing prediction task before and after the observation of an expert dart thrower. The outcomes of this dart thrower's actions (i.e., where darts landed) were only visible in the observation phase. Importantly, during this action observation phase, participants' motor systems were engaged to allow for the determination of core characteristics of the action simulation process. The results suggest that some types of motor system engagement reduce action prediction capabilities. Interestingly, significant inverse correlations were found between physical effort during motor engagement and action prediction accuracy.

Experiment 4 investigated the theoretical common coding between the visual and motor systems by assessing the relative impacts of visual and nonvisual motor training on action outcome prediction. Participants completed the action prediction task from Experiment 3 before and after performing visual or nonvisual motor training. In the nonvisual training condition, participants physically performed dart throwing while their vision of their throwing arm was occluded. In the visual training condition, participants physically performed dart throwing with full vision of their throwing arm. Lastly, in a control condition, participants played basketball. Participants in the nonvisual motor training condition demonstrated the largest gain in visual sensitivity in the action prediction task.

In conclusion, while the results of these experiments lend partial support for the common coding theory in general, they do not differentiate between specific perception-action coupling theories. Nonetheless, the current results do raise important questions about the generalizability of simple motor action studies to more complex, real world actions. Additionally, exciting future directions are revealed by the results of these experiments.

Dedication

This dissertation is dedicated to my late mother, Karen Blanchard. I miss you every day and some days during this journey seemed impossible without you. Even before I could see it in myself, you realized my potential and encouraged me to reach for my dreams. Your strength and love resonates in me now and has provided me with the means to face adversity and triumphs graciously. You taught me to be bold, open-minded, and compassionate which has carried me to this point. My heart swells with pride as I finish this chapter in my life because you recognized I could do this. I love being your daughter and you are with me every minute of every day.

Acknowledgments

There are so many people who deserve a great deal of thanks for helping me make my dissertation dreams become reality. I would like to thank to my advisor Maggie Shiffrar for giving me the freedom to explore my intellectual curiosities and in the process giving me support and encouragement. To me, you will always be inspiration and role model. A very special thank you goes to my other advisor, Robrecht van der Wel. Asking you to join me in this journey was one of the best decisions I have ever made. I thank you for your advice, your expertise, and your kindness. Thank you to my committee members, Vanessa LoBue, Eebie Tricomi, and Gretchen van de Walle for your wisdom, supervision, and most importantly receptiveness. There are many other people who helped me complete my dissertation studies along the way. I would like to thank Joseph Romanides, Leah Jeffery, and Kamila Redziniak for running an improbable number of participants in a fleeting amount of time. Thank you to John Franchak Sr. for his technical support and a friendly conversation every morning.

These studies would not have been possible without the help of James Thomas and Steve Ivory. I am so lucky my friends know how to wield power tools! Above and beyond your knowledge of construction, your friendship is invaluable to me. Thanks to both of you for simply being you. I would also like to thank other members of the Visual Cognition lab, Christina Joseph and Adam Doerrfeld. Christina, I am so proud of you and I am so fortunate to have you as my friend as well as my peer. To Adam, you will always be my big bro. Thank you to Jacob Duijnhouwer for your Matlab expertise.

Finally, my family deserves an enormous thank you. Thank you for your support (monetary as well as loving), giving me a place to escape, and helping me keep hope alive. To my precious nieces, Alexandria and Olivia, your worlds will open up if you work hard and dream big.

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Chapter 1: Introduction to Experiments 1 and 2

Watching other people move is a critical step not only for social reasoning such as determining a person's mood state or intentions, but also for learning new motor skills. Imagine attempting to learn how to perform a difficult motor skill such as a back handspring. A back handspring is a common gymnastics skill in which the gymnast jumps backwards from the feet onto the hands and then "springs" from the hands upright to the feet. The anxiety of launching one's body backwards with the hope of your arms not giving out on you is complicated enough without the threat of possible injury. When we want to learn new motor skills, there is an enormous benefit to observing an instructor perform the skill. You can observe the instructor in a step-by-step manner, while the instructor points out the important features of the skill to help improve your chances of successfully (and safely) performing the back handspring.

Granted, most people are not attempting to become a gold medal gymnast. However, observing others' actions for the purpose of improving the motor execution of our own actions is pivotal in many facets of life. Imagine, for example, getting a job as a barista at your local coffee shop. Making the different types of coffee delights takes practice, especially under conditions of high volume when sleepy customers require that cup of joe before they head to work. Even in this example, it works in your favor to learn how to make different coffee drinks by observing a more experienced barista. If by observing the experienced barista you can learn to make coffee drinks more efficiently, then you will be able to get the drinks to your customers faster, and as a result you will most likely keep your new job.

The overarching goal of this research program is to comprehend the underlying processes through which we acquire motor skills by observing others. To this end, the individual contributions of visual information and motor information to observational learning will be examined separately.

1.1 Observational Learning in the Laboratory

Observational motor skill learning has been defined as the ability of observers to adapt and improve their own movements by observing a model (Carroll & Bandura, 1982; 1985). Experiments 1 and 2 of this dissertation explore the benefits of observation in learning to throw darts. Previous research has shown that observational learning is possible in a variety of different motor tasks. In a recent review paper (Vogt & Thomaschke, 2007) that examined research on observational motor learning, different types of experimental motor tasks were grouped into five categories: sequence learning, timing tasks, configural actions, inter-limb coordination tasks, and dynamic tasks. I will review relevant findings for each of these topics in turn.

1.1.1 Observational sequence learning.

Sequence learning tasks often focus on the observation of a model performing a series of finger taps. For example, Heyes and Foster (2002) demonstrated observational learning effects using a serial reaction time (SRT) task. The SRT task requires participants to respond to a sequence of stimuli on the computer screen with corresponding button presses, such that one particular stimulus is related to the particular finger a participant uses to respond. On each trial, a stimulus is presented at a particular location on the screen (e.g., far left) and the participant responds with a button press with the appropriate finger (e.g., index finger on right hand). After a delay, the next stimulus is presented. In motor skill acquisition studies, three experimental phases are implemented: familiarization, training, and testing. The goal is to introduce, without the awareness of the participant, a repeated sequence of finger taps (ranging from 6 to 12 trials). Learning is assessed by a reduction in reaction time to physically performed sequences previously presented in the training phase, and a sharp increase in reaction time during the test phase whenever unlearned sequences are presented. In the research of Heyes and Foster (2002), all participants started by performing the finger tap task in order to familiarize them with the procedure. In the training phase, participants either physically practiced performing the finger tap task with the repeated sequence (physical practice group), observed the experimenter performing the finger tap sequence with the repeated sequence (observational practice group), or performed unrelated tasks (control group). During the subsequent test phase, reaction time was elevated (which signifies learning in part with the reaction time decrease during training) in both the physical practice and observation practice groups as compared to the control group (Heyes & Foster, 2002). Further research revealed that this observational learning of finger tap sequences is effector dependent (Bird & Heyes, 2005). Thus, for example, when observing an experimenter perform the SRT task with their fingers, participants did not demonstrate observational learning effects when asked to perform the same task with their thumbs.

1.1.2 Movement timing and observation of models.

Movement timing has been explored in observational learning tasks as well. Blandin and colleagues (1999) examined whether motor skill learning could occur when observing the relative timing of a series of movements. The task they employed required observers to watch a model move his/her hand from a starting point to a series of three barriers and then to a finish point. The barriers varied in their distance from the starting point and in their lateral position relative to the starting point (either left or right). The models performed this motor task in less than 900ms under two different timing conditions: natural timing (a control condition in which the time to move between barriers was not equal but what felt comfortable to the models) and constrained timing (in which the model moved between each set of barriers with equal timing even though the inter-barrier distances differed). In addition, there were two types of models: a beginner model with no significant experience with the motor task and an advanced model who was a percussionist (drum playing was assumed to be similar to the to-be-learned task in this study).

The participants were randomly assigned to one of the three experimental conditions: observation of the natural timing performed by a beginner model, observation of the constrained timing by a beginner model, or observation of the constrained timing by the advanced model. First, the partcipants completed a baseline measurement of physical performance in the natural or constrained timing task depending on the group assignment. Then, participants watched the model (either the beginner or advanced model) perform the task. After the observing the models, participants physically performed the same task as in the baseline measurement.

Participants were able to learn the constrained timing pattern after observing either the advanced model or beginner models. Participants who observed a beginner model perform in the natural timing condition showed learning of the natural timing but no learning of the constrained timing pattern. Thus, these authors concluded that observation of a model in combination with minimal physical practice promotes observational motor learning of constrained movement timing. However, aspects of the experimental design and finer grained details in the results raise some questions about the results drawn by Blandin and colleagues (1999). For example, in their first experiment, participants physically performed the constrained timing task best after observing the advanced model, while in the second experiment there were no differences in performance across model type. Furthermore, the advanced model was not an expert at the experimental task per se, but only with a related task. Thus, the fact that Blandin and colleagues (1999) did not consistently find a difference in observational motor learning across the beginner and advanced model conditions may reflect the fact that their advanced model was not an actual expert at the experimental motor task.

More recently, the comparison of the benefits of model type were examined by Rohnbanfard and Proteau (2011) using a similar relative timing task. These authors speculated that if expert models provide observers with a template of accurate and consistent performance and if novice models allow observers to scrutinize errors in motor performance then observing both an expert and a novice within the same observational period should optimize the benefits of observational learning. Participants in this experiment performed the timing task described above except that they were required to complete the task in 1200ms, allowing 300ms to reach each barrier. After an initial familiarization phase (with no feedback on motor performance), participants viewed a video of a novice model, an expert model, or a combination of a novice and expert models perform the task for 60 trials. As a control condition, a group of participants simply read a newspaper during the same amount of time as the video condition. Testing for observational motor learning effects included three time points (immediately after the observational manipulation, 10 minutes after, and 24 hours after) to examine retention and transfer of the timing task. Retention of the learned task was assessed by asking participants to reproduce the timing task in 1200ms, allowing for 300ms between each barrier. Transfer, on the other hand, required participants to complete the timing task in1500ms but with the same relative timing between barriers.

The results showed that, immediately after the observational manipulation, all of the observation groups demonstrated improvement for retention and transfer as compared to the control group. At later test points (10 minutes after and 24 hours after the manipulation), the observation of an expert model or combination of an expert and a novice model led to improved performance in the task as measured by retention of the learned task. At these test points, the observation of a novice model alone resulted in participants performing with greater variability, unlike the other observation conditions. Lastly, the results suggest that participants in the mixed observation group demonstrated superior transfer of the learned skill compared to the other groups. The authors concluded that observing both types of models is most beneficial to observational learning. This study presents an interesting alternative to examining the single most beneficial type of model (expert or novice) for observational learning. However, to make the claim that observing the juxtaposition of an expert model's accurate performance and a novice model's error correction is most useful for observational learning requires that two other possibilities are addressed. First, this study does not rule out the possibility that observing any type of task-related stimulus might influence an observer's subsequent performance. In other words, would observing a novice who does not improve at the task throughout the observation phase influence an observer's performance of the same task? Secondly, the observation of a model in order to improve one's performance in a motor task should be task dependent. Although not included in Rohnbanfard and Proteau (2011), participants in this study should not improve if they were to observe a model performing a different type of motor task, irrespective of model type (expert or novice). The primary goal of Experiments 1 and 2 in this dissertation is to address these two issues directly. To that end, the impact of model type on observational motor learning will include conditions in which participants view a novice model who consistently performs the motor task poorly (i.e., does not improve) and view a model who performs an unrelated motor task.

1.1.3 Configural actions and observation of models.

Configural action tasks involve motor learning through the observation of the positions and movements of body parts relative to one another to accomplish some motor goal. Research in this subfield has explored skills such as learning guitar chords (Buccino et al., 2004) and dart throwing (Al-Abood et al., 2001). Al-Abood and colleagues (2001) aimed to answer the question of whether observers can learn to throw darts accurately by watching the relative arm motion information of a novice dart thrower conveyed in full light videos and/or by point-light videos. Novice models were filmed while training on a novel underarm dart throwing task. After extensive training and significant improvement in their underarm dart throwing performance, the resultant videos were edited to select out the most accurate throws. These videos were also analyzed so as to extract the models' spatial and temporal coordinates of their arm throws in order to compare their throws with the observers' subsequent dart throwing performance. The results of the study by Al-Abood and colleagues (2001) revealed that, after observation, participants in both the full light and point-light movie conditions produced patterns of multi-limb coordination that resembled the coordination patterns of the models. These authors concluded that relative limb motion information is preserved in point-light displays and is sufficient for observers to extract the configural limb information needed to improve their own motor performance.

Experiments 1 and 2 of this dissertation differ from the study by Al-Abood and colleagues (2001) by measuring motor performance outcome measures (accuracy and precision) of dart throwing actions as opposed to evaluating limb motion during dart throwing. However, if participants' limb motions approximate those of the dart throwing models they observed, as demonstrated by Al-Abood and colleague (2001), then the motor outcome measures of participants in Experiments 1 and 2 below should also approximate the models' motor outcome measures.

1.1.4 Observational learning of coordination skills.

The effects of observing a model learning a novel skill have also been studied using inter-limb (Maslovat et al., 2010) and single-limb (Buchanan et al., 2008) coordination tasks. However, the experimental results in this subfield make it unclear whether observation enhances subsequent motor skill performance. Many observational learning studies include the observation of a model interspersed with physical practice. Recently, Vogt and Thomaschke (2007) defined "observational practice" as a separate type of motor learning paradigm distinct from observational learning. Observational practice relies on pure observation without physical practice to inform motor learning. Observational learning, on the other hand, employs observation of a model interspersed with physical practice of the to-be-learned motor skill.

Maslovat and colleagues (2010) examined the differences in physical performance of a bimanual coordination task after physical practice (only physically performing the skill) or observational practice (only observing a model perform the skill). The coordination task required participants to place their hands palms down on a table and then rotate them according to the stimuli on a nearby monitor. Participants would rotate both hands in towards their body (in-phase coordination), rotate both hands to the left or right (anti-phase coordination), or a rotation pattern representing somewhere between in-phase and anti-phase coordination (relative phase coordination). The relative phase coordination pattern was an intermediate pattern between the in-phase and anti-phase coordination patterns. The experimental procedure was conducted over four days. On the first day, all of the participants physically performed the bimanual coordination task at one various phases described above and then a perceptual discrimination task after each trial. In the perceptual discrimination task, participants tried to identify the relative phase that was previously performed by identifying which hand was leading in the rotation. After the first day of the experiment, half of the participants were assigned as “model” participants and the remaining participants were assigned as “observer” participants. During the subsequent two days, the “model” participants physically practiced the bimanual coordination task while “observer” participants looked on. Finally on the fourth day, performance accuracy in the bimanual coordination task was assessed for all participants (models and observers) and after each trial of the coordination task participants performed the perceptual discrimination task for the preceding hand coordination trial. Only model participants demonstrated improved physical performance of the task in the post-test assessment. Conversely, participants who only observed a model perform the hand rotations did not show motor improvement. However, both the model and observer participants improved in the perceptual discrimination task, such that both were better able to identify different relative phase coordination patterns (the intermediate pattern).

It may be the case that motor performance did not improve for the observers in this study by Maslovat and colleagues (2010) because throughout the experimental procedure participants who only observed the models were not required to observe and practice the task on the same day. Thus, on days when the observer participants watched a model, they were participating in an observational practice paradigm, not an observational learning paradigm (observation of a model interspersed with physical practice of the motor task). Buchanan and colleagues (2008), however, did find that pure observation lead to an improvement in the motor performance of a single-limb coordination task. If the experimental designs in Maslovat and colleagues (2010) and Buchanan and colleagues (2008) were modified to include observation and physical practice (observational learning paradigm) within the same training session, improvements in motor skill acquisition may be more consistent across these experimental paradigms.

1.1.5 Observational learning in dynamic environments.

Observational learning studies focusing on task dynamics manipulate the environment in which motor skill learning takes place. In a notable demonstration of this by Mattar and Gribble (2005) (also see Brown et al., 2009), participants observed a novice model learning to maneuver a robotic arm towards different targets in a variable force field. Typically we learn complex motor skills by observing experts (e.g., coaches or players), however, novices may provide better information for the initial learning of a novel motor skill because, in part, they afford more information on error correction. Furthermore, as will be discussed later, novice models also execute motor skills that are, by definition, similar to the motor abilities of novice observers and thus may be easier for novice observers to map onto their own motor repertoire. For example, the novice models in the Mattar and Gribble study (2005) were inaccurate and imprecise when they first performed the robotic arm task. However, with more trials of physical practice, the novice models were better able to control the robotic arm and consequently became more accuracy and precise with their movements. This pattern of increasing motor precision may be important for a novice observer to learn how to perform an observed task more accurately, similar to the novice model.

After observation of the novice models, participants performed the same task themselves in force fields that were either congruent or incongruent to the force fields in which the observed model had moved. Accuracy was better when the felt force field was congruent with the observed force field. Mattar and Gribble (2005) concluded that observational learning in dynamic environments is possible and that observers can benefit from observing a novice model performing a motor task in an environment that approximates their performance environment.

To determine further if better motor performance in congruent force fields is reliant on the activation of motor areas during observation, participants performed unrelated arms movements during the observation phase (Mattar & Gribble, 2005). The ability to accurately move the robotic arm sharply decreased when participants performed unrelated arm movements during observation of the novice model a finding that conforms with previous research on motor interference (e.g., Reed & Farah, 1995; Witt et al., 2010). Important, no such decrease in motor performance was observed when participants performed a mathematical distraction task while they observed the model moving the robotic arm in various force fields. The results of this “non-motor” control condition, in conjunction with the results from the motor interference condition, are important because they suggest that motor learning through observation requires significant engagement of the observer’s motor system. This is in line with perception-action coupling theories (Gibson, 1979) and with the proposed neural correlates of perception-action coupling (Rizzolatti et al., 2001; Rizzolatti & Craighero, 2004) which are discussed below.

This review of observational motor learning research highlights the debate over the superior model type during observation in order to more efficiently learn a novel motor skill.

However, without a comparable expert model in the Mattar and Gribble (2005) study, it remains unclear what type of visual information is more useful during observational motor learning. Unlike novice models, expert models demonstrate consistent performance with uniformly, or nearly uniformly, high accuracy and precision. Novice observers may learn novel motor skills more quickly by observing experts' consistently good performance of the to-be-learned motor skill. At present, there is no clear answer as to whether observational learning is faster during the observation of novice or expert models. Indeed, as summarized above, past research has shown mixed results concerning the benefits of different types of models on observational learning (i.e., Blandin et al., 1999; Al-Abood et al., 2001). Some research has suggested that there is no benefit to observing an expert model over a novice model or vice versa (Blandin et al., 1999) where as other research suggests that observing expert models enhance observational learning effects (Al-Abood et al., 2001).

1.2 Perception-Action Coupling: Theories and Neural Correlates

There is plenty of debate in the field about how motor skills are learned through observation. The link between perception and action was elegantly emphasized by J. J. Gibson when he asserted that, "We must perceive in order to move, but we must also move in order to perceive." (Gibson, 1979, p. 223). Gibson claimed that perception and action are reliant on one another, and that control is dictated both by movement and perception of the self in the world. On a more elementary level, if we were to stop moving and fixate on an object, our vision of the objects in the periphery would literally fade away, a phenomenon known as the Troxler fading effect (Troxler, 1804). Thus, perception and action are typically understood as coupled.

Many theories of perception-action coupling now contain a cognitive representational component. Such theories posit that perceived action generate representations that share commonalities with the neural representations used in generating motor actions (Prinz, 1997; Hommel et al., 2001; Jeannerod & Jacob, 2005). In the action understanding literature, Rizzolatti and colleagues (2001) have proposed that the representations of observed actions are directly matched to the representations of the observer's motor repertoire in a bottom-up fashion. The visual representation of an observed action overlaps with a motor representation of the same action, leading to action understanding at a higher representational level in the observer.

Some support for this direct matching theory comes from the discovery of mirror neurons. Originally discovered in macaques, single neurons in the premotor cortex, specifically area F5 of the premotor cortex in monkeys, fire to both performed object-directed actions and identical observed actions (di Pellegrino et al., 1992). To test if the human brain contains mirror neurons, Fadiga and colleagues (1995) used transcranial magnetic stimulation (TMS) to create a temporary, virtual lesion in the motor cortex which is extensively connected to the premotor cortex. These researchers reasoned that if the premotor cortex of the human brain did contain mirror neurons, then action observation alone should be sufficient to trigger activity in the observer's motor cortex. Despite the virtual lesion to the motor cortex, motor evoked potentials (MEPs) increased in participants' hands when they observed another person grasping objects compared to when they observed the objects alone. Furthermore, the MEPs detected in the hand muscles during the observation trials were identical to the hand muscles used to grasp objects suggesting an overlap between brain areas for action execution and observation. In other words, the observation of hand grasping was directly matched to the participants' hand grasping motor representations, leading to increased activity in the hand muscles. Activation of motor representations by observation of hand grasping has been said to denote the covert stage of action execution, while the overt stage is represented by physical performance (Jeannerod, 2001) as evidenced by the increased activity in the hand muscles.

Evidence of the relationship between action production and observation has also been documented in imitation studies. Similar brain activations occur during both performed and observed actions; however, imitation requires both performing and observing an action simultaneously. Thus, imitative actions should elicit stronger brain activations than execution or observation of action alone. Iacoboni (1999) found that imitating finger taps (concurrent execution and observation) increased activity in areas that have been associated with the mirror neuron system (e.g., inferior frontal gyrus and inferior parietal lobule) as compared to neural activity during observation only or action execution to symbolic cues. Unlike the macaque studies, no object manipulation was necessary for mirror neurons to fire in human participants as long as an intention to reproduce/produce a movement was present.

It has been argued that areas implicated in the mirror neuron system through methods including PET and fMRI that cannot provide evidence for mirror neuron properties at the single cell level (Dinstein et al., 2007; 2008). While BOLD signals, for example, may demonstrate overlaps in areas active during action observation and action production, this does not mean that the same neurons are active during both instances. Furthermore, during imitation studies (i.e., Iacoboni et al., 1999) a host of other brain areas are activated, not limited to areas involving in the mirror neuron system. To address this methodological problem, Kilner and colleagues (2009) employed a repetition suppression paradigm with fMRI used in previous studies (e.g., Dinstein et al., 2007). It was reasoned that if the activation of neurons thought to be part of the mirror neuron system, specifically the inferior frontal gyrus, decreases through repeated exposure, it should not matter if the exposure comes from action production, action observation, or importantly, a combination of both. Participants were exposed to videos of two types of hand movements and asked to also perform these same movements in alternating order. The results demonstrated that adaptation occurred when the participants first viewed hand movements and then subsequently performed the hand movements, and vice versa. Kilner and colleagues (2009) concluded that these results are only possible with within a mirror neuron system or, more generally, within a system in which perception and action are coupled.

The human homologue of area F5 in macaques has been posited to be the inferior frontal gyrus, including Broca's area (Kilner et al., 2009; Buccino et al., 2001) which is implicated in mouth movements during speech (Rizzolatti et al., 1996). Buccino and colleagues (2001) aimed to determine if activation in Broca's area during action observation was due to internal verbalizations and further to determine if the mirror neurons were specific to mouth movements. To do so, they used fMRI while participants observed object-directed and non-object directed actions with the mouth (e.g., chewing an apple), the hands (e.g., grasping a cup), and the feet (e.g., kicking a ball). Non-object directed actions were the same actions without the object present. Buccino and colleagues (2001) found that the mirror neuron system was active to actions beyond just the mouth, and that the premotor cortex was somatotopically organized in a similar fashion to the motor cortex homunculus. These findings rule out the possibility that mirror neuron activity is due to internal verbalizations when observing the actions of others. Furthermore, parietal mirror neuron activity appeared to be most pronounced during the observation of actions with objects. Overall, this would suggest that all of the mirror neurons in the network of brain areas are not created equal; in other words, different parts of the mirror neuron system are specialized for specific body parts and different types of actions.

Neural activity within the mirror neuron system appears to differentiate observer's intentions towards observed actions. Decety and colleagues (1997) used PET to examine patterns of brain activations during the observation of meaningful actions (e.g., miming opening a bottle) and meaningless actions (e.g., American Sign Language (ALS) in participants unfamiliar with ALS). Participants observed each action with the intent to either recognize the action later or imitate the action later. The results suggested that the intention of the observer modulates activity in action planning areas such that when intending to imitate the observed action, more action planning areas, such as the dorsolateral prefrontal cortex and the premotor cortex, are active. Similar results were found in a follow up study (Grezes et al., 1998).

While the mirror neuron system, or the more agnostic term the “action observation network” (Cross et al., 2009), is far from fully understood at this point, there does appear to be a clear relationship between action execution and action observation on a neural level. Direct matching theory (Rizzolatti et al., 2001) speculates that the observation of an action results in a visual representation that overlaps with motor representations by way of the mirror neuron system, leading to action understanding. However, direct matching theories has been criticized for the fact that they do not account for instances in which similar actions have differing outcomes (Zentgraf et al., 2011). For example, one may observe someone reaching for a cup with the intention of drinking from it or handing it to someone else. In this case, the same action could be directly matched to several different action outcomes. This inherently ambiguity obviously complicates action understanding.

An alternative way of looking at action understanding is through an action reconstruction point of view (Csibra, 2008). Essentially this theory posits that observing an action results in a high-level representation of a goal state, and in order to achieve that goal state, the observer may use different kinematics (lower-level representations) to attain the same goal. Again, using the example of observing someone reach to and pick up a cup, we can clarify the difference between direct matching versus action reconstruction. In this example, direct matching assumes that the visual representation of the person picking up the cup first is cognitively represented on the level of motor kinematics (i.e., type of grip used on cup). Then, this representation is directly matched to the motor representation of the observer, resulting in a higher-level representation of the purpose of the observed action (i.e., to take a drink from the cup). On the other hand, action reproduction assumes that the visual representation of the actor picking up the cup is produced in a higher level of representation such that the goal can be inferred (i.e., to take a drink from the cup). From this higher-level representation, action reconstruction can occur such that a motor representation of the observer is activated to perform the same action (i.e., use a particular grip on the cup to take a drink). However, the same kinematics as those observed are not necessary to achieve the same goal.

1.3 Overview of Experiments 1 and 2

In sum, there is evidence to suggest that the visual system is tightly linked to the motor system. This linkage has been demonstrated not only at the neurophysiological level but also with the phenomenon of observational learning. The overarching goal of the four studies described in this dissertation is to better understand the contributions of visual and motor experiences to observational motor learning. The first two experiments (Experiment 1 and Experiment 2) examine the influence of model expertise on observational learning. The last two experiments (Experiment 3 and Experiment 4) aim to show that predicting action outcomes relies on the quality of the perception-action connection.

Experiment 1 and Experiment 2 explores the visual information that observers use when learning to perform a complex motor skill by watching someone else perform that skill. More specifically, Experiments 1 and 2 were designed to determine whether observational motor learning is best facilitated when observers view novice or expert models performing the to-be-learned task. Previous research has shown observational learning is possible through watching both experts and novices (see Blandin et al., 1999; Mattar & Gribble, 2005). But which model impacts advancement to a larger degree in observational motor learning for novice observers? Rohnbanfard and Proteau

(2011) showed that observing either model is immediately valuable but observing a novice model may not provide longer term benefits to learning a motor skill. However, specific control conditions were not included in this study to rule out alternative explanations. Observing a novice model learning a new complex motor skill may improve the observer's ability to perform the same skill, as novices provide extensive information regarding error correction because they produce more errors. Consistent with this line of reasoning, direct matching theories (Rizzolatti et al., 2001; Rizzolatti & Craighero, 2004) predict that when the observer and the model are at the same skill level (e.g., both novices), then the observer should be better able to match the observed actions of the model onto representations of his or her own motor repertoire. This, in turn, might facilitate observational motor learning. Observing a novice model who does not demonstrate motor skill improvement should not influence motor learning in the novice observer because errors are not corrected (Experiment 1). On the other hand, observational motor learning may be superior when novices observe expert models who demonstrate consistently accurate and precise motor performance. If the observer benefits more from observing an expert model, this would suggest that observational motor learning emerges from action reconstruction (Csibra, 2008). Novice observers should struggle when attempting to directly match the actions of experts onto their own motor repertoire. Thus, if observational motor learning occurs after observation of an expert model, then novice observers must have used their own kinematics to achieve this goal. Consistently accurate and precise performance of an expert model should only be useful if it is the same task the observer is expected to physically perform (Experiment 2).

Chapter 2: Observational Learning and Model Expertise

2.1 Experiment 1: Observational Motor Learning with a Novice or an Expert Model

2.1.1 Hypothesis and theoretical motivation.

The current study was designed to measure observational motor learning with dart throwing. While previous research has shown that observational learning can occur with both novice and expert models, few studies have attempted to compare these models against one another (for an exception, see Rohnbanfard & Proteau, 2011). Each model type offers different kinds of information as novice models afford the observer information on error correction while expert models afford information on motor skill accuracy and precision. Experiment 1 investigated the benefits of each models' unique motor skill distinctions but also added a control condition to ensure that simply observing a model performing dart throwing (without improvement) does not impact observational learning.

Experiment 1 aimed to determine the optimal model for observational motor learning. The experimental paradigm features a dart throwing task in spirit of Al-Abood and colleagues (2001) and Knoblich and Flach (2001). Stimuli consisted of videos depicting dart throws edited to accentuate three different features: error correction (i.e., an improving novice model), accuracy and precision (i.e., an expert model), or inaccuracy and imprecision (i.e., an unimproving control model). At the start of the study, participants were asked to physically perform dart throwing (baseline performance measure). Then they were assigned randomly to one of the three different observation conditions (model manipulation). After the observation phase, participants again physically performed the same dart throwing task. The key measure was the magnitude of change in dart throwing accuracy, from initial baseline performance, as a function of whether the participant viewed, during the observation phase, an improving novice model, an expert model, or an unimproving novice control model.

According to the direct matching theory (Rizzolatti et al., 2001), matching the visual representations of seen dart throws to one's own motor repertoire should be best with novice models (as all of the participants are dart throwing novices). To the extent to which this process impacts subsequent dart throwing ability, participants should learn the most and, as a result, perform best after observing novice models who *improve* during the observation period. A novice observer monitoring a novice model with consistently poor dart throwing abilities would also be able to match those visual representations onto his or her own motor repertoire. However, learning how to throw darts poorly should not improve a participant's dart throwing abilities. This is a key distinction of Experiment 1 as compared to previous research. We expect that the participants who observe a novice model performing poorly throughout the duration of the observation phase should not demonstrate improvement in dart throwing.

On the other hand, participants may show more improvement after observation of an expert model. It is unclear how direct matching theories could readily account for this result because there is an inherent mismatch in this condition between the participants' motor repertoire and the model's motor abilities. If participants show more improvement after observation of the expert model, then action reconstruction theory (Csibra, 2008) may be best foundational underpinning for observational motor learning. Expert models perform a motor skill with a level of accuracy and precision that surpasses the novice observer's motor repertoire. Improved dart throwing performance by novice participants after observation of the expert model would suggest that some key feature(s) of the observed motor skill were represented in the naïve observer's motor repertoire, likely at a higher cognitive level, and were available to assist in the creation of specific kinematic motor commands that the novice participant could employ to become more accurate and precise in their dart throwing.

2.1.2 Methods.

Participants. Thirty-one Rutgers University – Newark undergraduate students (mean age = 20.52 years old; 15 males and 16 females) participated in the study for partial course credit. All of the participants had normal or corrected to normal vision and reported that they were dart throwing novices. Of the participants, 29 were right-handed throwers and two were left-handed throwers. All of the studies presented in this dissertation, including Experiment 1, were approved by the Rutgers University IRB and all participants provided written informed consent.

Materials. Participants were asked to throw 25 sets of darts (three darts per set) at a paper archery target taped to a regulation size dart board. The darts were Harrows brand steel tip darts weighing 24 grams. The Maple Leaf FITA target face archery target measured 40cm in diameter and featured 11 concentric rings of various colors. The area at the center, or bull's eye, of the archery target was yellow. This central yellow region was used as the target goal in the dart throwing task (Figure 1). The use of a paper archery target allowed for easy data storage and provided a larger than normal area (as compared to the bull's eye of a dart board) at which the participants could throw their darts—an important consideration because all participants were novice dart throwers.

In the observation phase of this experiment, participants viewed one of three possible videos. The raw footage for the videos was shot with a Canon HD VIXIA HF20 digital video camera. The videos depicted either an expert dart thrower who hit the yellow goal area consistently and accurately throughout the video (a total of 45 times out of 75 dart throws), a novice dart thrower who improved over the duration of the video hitting the yellow target area more often towards the end (a total of 17 times out of 75 dart throws), or a control, novice dart thrower whose dart throwing accuracy was consistently poor and thus showed no improvement (a total of 7 times out of 75 dart throws). Each movie showed the models throwing 25 sets of 3 darts with the goal of hitting the yellow target area as often as possible. All of the movies depicted 75 throws and lasted approximately four minutes. In all three conditions, participants viewed the dart throwing videos on a Toshiba Satellite P770 laptop with a 17.3” diagonal HD backlit TruBrite display (60 Hz refresh rate, 1600 x 900 pixel resolution) using VLC media player from a distance of approximately 50 cm.

Figure 1. Depiction of archery target used in Experiments 1 and 2. The diameter across the largest ring is 40cm. The three yellow rings had a maximum diameter of 8cm. Participants were instructed to throw darts so that they landed at the center, in the yellow target area.

Model video construction. The expert dart throwing model had a total of six years of dart throwing experience and typically plays four times per week. The novice dart throwing model had no previous experience throwing darts. Both models were filmed from a 3/4 point of view that included both the dart throwing model and the archery target in the same shot. Raw footage was captured, individually, from both the expert and novice dart throwing models in a single two hour session. The raw footage was then edited (Adobe Premiere Pro v2.0) to create three videos of approximately four minute duration depicting a model throwing 25 sets of 3 darts at the same stationary target.

The expert video was created by first identifying the most accurate sets of dart throws. Accuracy was defined as the average distance (in mm) from the center of the target's bull's eye for each of the three darts in each set. Once the most accurate sets were identified, the expert video was edited to depict only the 25 most accurate sets of dart throws. In the edited video, each set began before the expert model lifted his arm in preparation to throw the first dart in that set. A set would end after the third dart in the set hit the target. On the computer screen, the model subtended approximately 9.65 degrees of visual angle (DVA) in height and 10.76 DVA in width when the model's arm was extended.

The two remaining videos ("novice improve" and "novice worst") were constructed from the same raw footage of the novice model. First, the accuracy of the novice model's dart throws was determined by coding the colored ring in which each of the three darts from each set landed on the archery target. Very inaccurate dart throws landed in the black rings or in the most peripheral white area of the target or missed the target entirely. Dart throws with intermediate accuracy landed in the blue or red rings while the most accurate dart throws landed in the yellow. The "novice improve" video featured sets of dart throws at the beginning of the video that were very inaccurate (including dart throws that completely missed the target). As the "novice improve" video progressed, sets of dart throws became more accurate and this video ended with accurate dart throws near the bull's eye. For example, at the beginning of the video the novice model was shown throwing a set of darts in which one dart missed the target, the second dart hit the white rings, and the third dart hit the black rings. At the end of the "novice improve" video, the novice model was shown throwing a set of darts in which all three darts hit the yellow target area. There were equal numbers of inaccurate dart throws, intermediate dart throws, and accurate dart throws (see Figure 2). During the Experiment 1 described below, when asked by the experimenter to describe each model's dart throwing behavior, participants viewing the "novice improve" video readily recognized the model as improving over time. This “novice improve” video was constructed based on the assumption of perception-action coupling theories that novice participants should be able to match directly perceptual representations of other novices’ actions with the motor (or perceptual-motor) representations defining their own motor repertoires. Further, there is useful information for novice observers in the “novice improve” video on how to enhance performance over time (error correction).

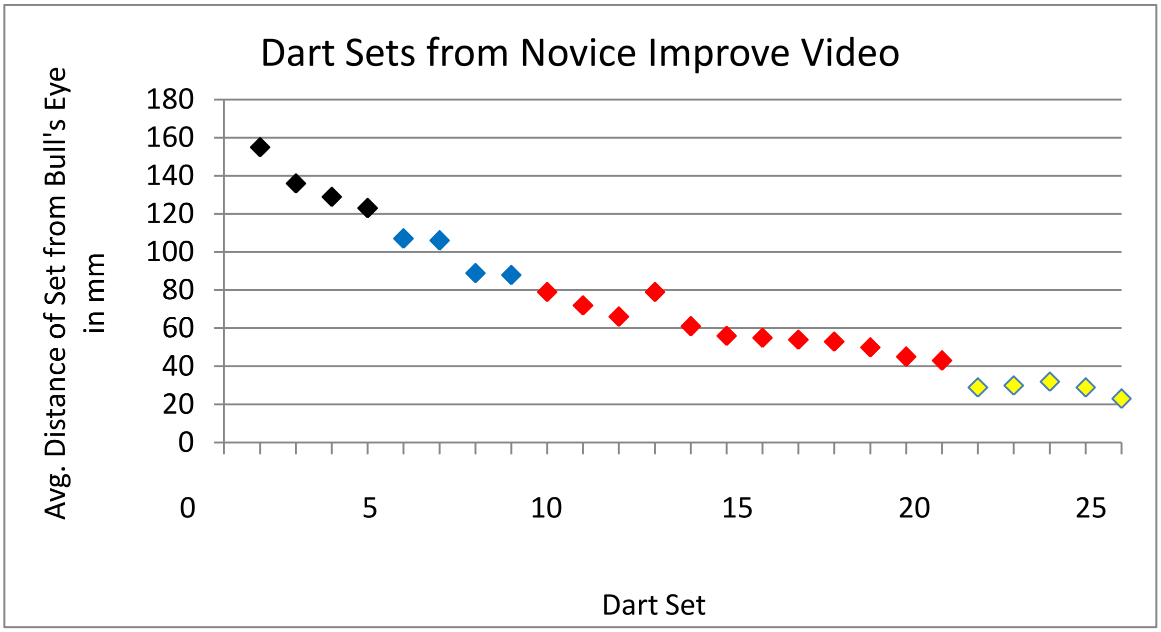


Figure 2. Landing locations of 25 sets of dart throws in the “novice improve” video as a function of the distance from the bull’s eye in millimeters. The first sets of darts were inaccurate and imprecise while the last sets of dart throws are accurate and precise and landed in the yellow. The colors of the data points represent the colored ring of the target (Figure 1) in which the average of the three dart throws in each set would land.

The “novice worst” video was essentially the opposite of the expert video and was meant to serve as a control condition. The novice model’s most inaccurate sets of dart throws were first identified and then edited into the final version of this video. The inaccurate dart sets included darts throws that landed far away from the bull’s eye, and also dart throws that missed the target completely or bounced off the target and fell to the ground. While in this condition novice observers should be able to directly match their visual representations of the dart throws to their own motor repertoires (as both the observers and the model are novices), this condition did not depict useful information on how to improve one's dart throwing skills. The model in the novice improve and novice worst videos subtended 10.43 DVA in height and 11.09 DVA in width with the model's arm fully extended on the computer screen.

Design and procedure. Participants were randomly assigned to one of three possible experimental conditions in this between-subjects design: The expert video condition (n = 10), the "novice improve" video condition (n = 11), or the "novice worst" video condition (n = 10). The experiment consisted of three phases in the same order: a familiarization phase, an observation phase, and a test phase (Figure 3).

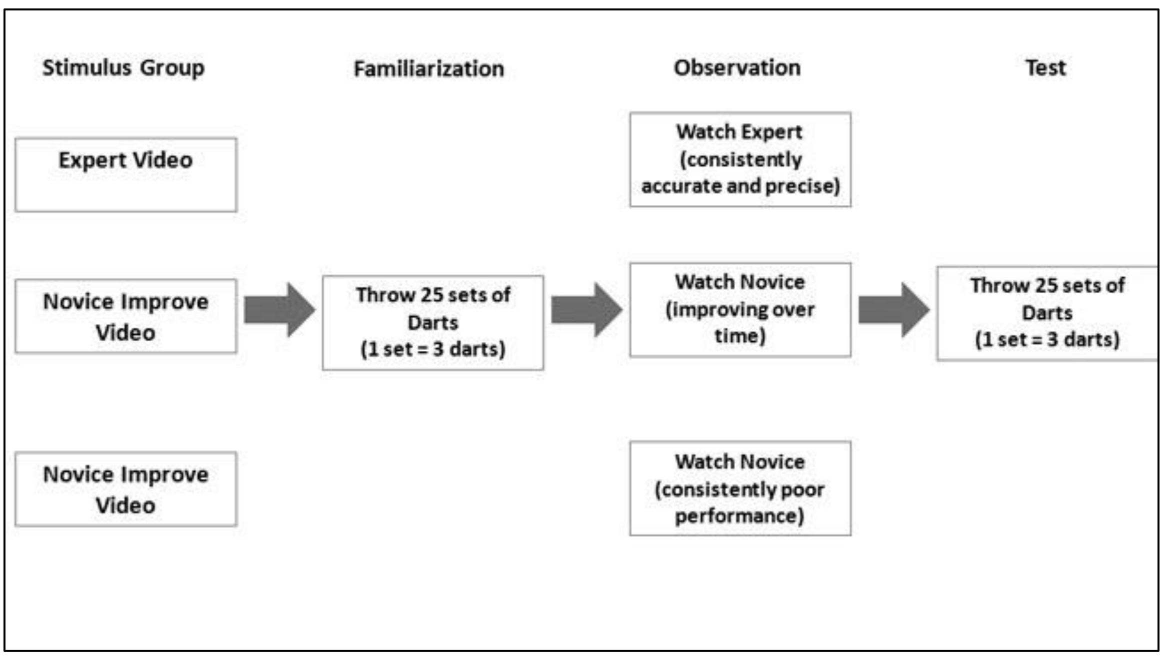


Figure 3. Experiment 1 design. Participants were assigned to one of three model conditions and then performed the familiarization, observation, and test phases.

During the familiarization phase, participants stood at regulation dart throwing distance (7 feet, 9 inches) from the target and physically performed 25 sets of 3 darts throws. Their goal for each throw was to hit the yellow bull's eye at the center of the target. The experimenter instructed participants to feel free to throw the darts in any way that felt comfortable to them as long as their feet did not cross the line marking the regulation distance. If the darts landed on the archery target once thrown, the experimenter numbered the darts appropriately as to which was the first, second and third dart thrown in each set. If any darts missed the target completely (but stuck to the backboard), these darts were marked as a "miss". If any darts hit the target or backboard but bounced off and landed on the ground, these darts were marked as a "bounce".

Following the familiarization phase, participants then completed the observation phase. Participants were seated so that their eyes were approximately 50 cm from a laptop display positioned on a table and watched one of the three dart throwing videos. During this observation phase, participants placed their palms on the table on either side of the computer. While watching their assigned video, participants were asked to attend to the model's dart throwing movement and the outcome of each dart throw. To ensure that the participants paid attention to the videos, they were required to report the number of darts landing in the yellow goal area at the conclusion of the video.

Following completion of the observation phase, the test phase was implemented. Participants again threw 25 sets of 3 darts with the goal of landing as many darts into the yellow goal area as possible. The participants again stood at the regulation distance from the dart board. The same coding scheme for darts landing on the target, backboard (miss) or ground (bounce) was used.

Analyzing the target data. In this experiment, the accuracy and precision of all dart throws in the familiarization phase and in the test phase were measured, by hand, individually with a ruler. First, accuracy measurements were taken by measuring the distance between the center of the bull's eye and the landing location of each individual dart. Then, the average accuracy of all a participant's dart throws in each set was calculated. Precision measurements were attained by measuring the distance of each dart throw from the other two dart throws in the set. These data were then averaged across each subject. Accuracy and precision data were obtained for each subject in the familiarization phase and in the testing phase (that is, before and after observing the model dart thrower). Figure 4 illustrates the accuracy and precision analyses.

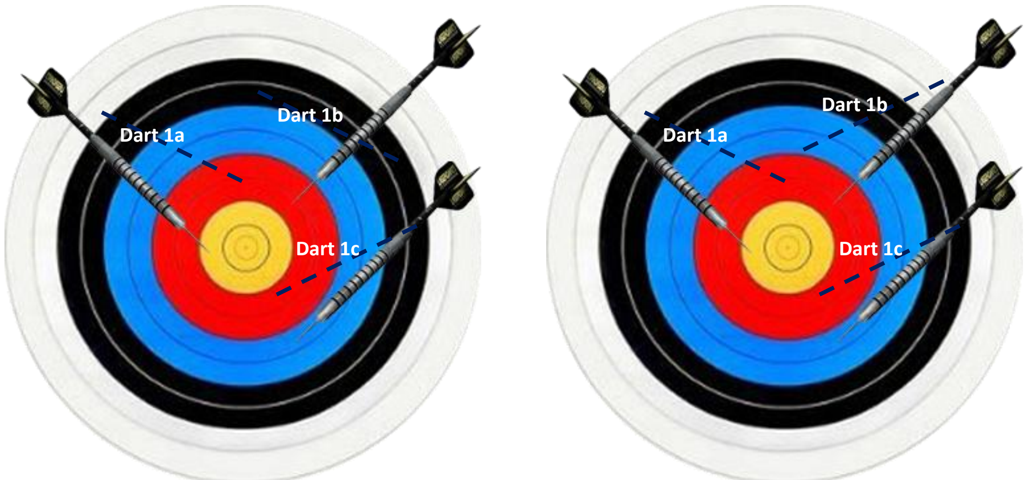


Figure 4. Illustrations of the accuracy (on left) and precision (on right) measurements in Experiment 1. Accuracy was defined as the average distance of each dart from the bull's eye from all 25 sets both before and after observation. Precision was defined as the spread of all dart throwing sets. The spread for each set of darts was the average distance a dart landed from the other two darts in the same set. For example, if the first set of darts, Dart 1a was approximately 70 mm away from Dart 1b and approximately 85mm away from Dart 1c, and Dart 1b was approximately 90mm away from Dart 1c, the average precision of this set of darts would be 81.67mm.

2.1.3 Results.

Table 1 depicts the average accuracy, the average precision, the average number of misses, and the average number of bounces from the familiarization and test phases by video condition. If direct matching occurs during the observation of the novice improve video, participants in this condition should demonstrate greater dart throwing accuracy and precision in the test phase than participants in either the expert or novice worst video conditions. However, if observational learning is facilitated by action reconstruction, then observation of the expert video should lead to more improvement in dart throwing accuracy and precision than observation of either the novice improve or novice worst videos.

Video Condition	**Accuracy Before**	**Accuracy After**	**Precision Before**	**Precision After**	**Misses Before**	**Misses After**	**Bounces Before**	**Bounces After**
Expert Video	**83.7** (SE = 7.88)	**77.34** (SE = 8.00)	**118.93** (SE = 10.95)	**102.86** (SE = 10.94)	**3.30** (SE = 1.26)	**1.80** (SE = .68)	**1.30** (SE = .50)	**1.30** (SE = .47)
Novice Improve Video	**95.23** (SE = 3.96)	**92.97** (SE = 5.28)	**127.09** (SE = 5.27)	**125.19** (SE = 7.89)	**1.64** (SE = .69)	**3.45** (SE = 1.05)	**.82** (SE = .44)	**.82** (SE = .33)
Novice Worst Video	**88.68** (SE = 5.17)	**81.81** (SE = 5.63)	**125.03** (SE = 8.42)	**114.76** (SE = 8.30)	**5.90** (SE = 1.64)	**2.50** (SE = 1.10)	**1.70** (SE = .62)	**.10** (SE = .10)

Table 1. The average accuracy, precision, misses, and bounces before and after the observation of the three video conditions. Accuracy and precision are measured in millimeters. Misses and bounces are the average number of errors before and after the observation phase.

Familiarization phase. First, to determine whether participants in the three video conditions differed significantly from one another in their dart throwing abilities before the experimental manipulation, one-way ANOVAs were run to analyze accuracy, precision, misses and bounces in the familiarization phase (before the observation of the expert or novice models) by each group. The results of the one-way ANOVAs confirmed that the participants in the different video conditions did not significantly differ from each other during the familiarization phase in dart throwing accuracy (F (2, 28) = 1.015, *p* = .375, n_p^2 = .068), precision (F (2, 28) = .257, *p* = .775, n_p^2 = .018), or the average number of bounces (F (2, 28) = .737, *p* = .487, n_p^2 = .050). However, there was a marginally significant difference in the average number of misses by video condition (F (2, 28) = 3.076, *p* = .062, n_p^2 = .180).

Post hoc tests revealed that there was a marginally significant difference between the participants in the “novice improve” condition and the “novice worst” condition (F (2, 28) = 3.076, *p* = .051) for the average number of misses during the familiarization phase. During the familiarization phase, participants in the “novice worst” condition missed the target (8% of trials) more frequently, on average, than participants in the “novice improve” condition (2% of trials). Given that misses were rare, statistical analyses of the number of misses by condition should be interpreted cautiously.

Dart throwing performance before and after video observation. To determine if the type of dart throwing model that participants observed influenced participants’ subsequent dart throwing performance, a series of mixed model ANOVAs was conducted on accuracy, precision, average number of misses, and average number of bounces before and after the observation phase. In all of these analyses, the between subjects variable was the model condition and the within subjects variable was dart throwing performance (accuracy, precision, misses, and bounces) from before relative to after the observation period. It is important to note that the lower number associated with dart throwing performance means that participants were more accurate and precise. A score of zero for accuracy and precision indicates that a participant hit the bull’s eye.

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Interaction of Time * Group**
F-test on Accuracy	$F(1, 28) = 9.228$, $\boldsymbol{p = .005}$, $n_p^2 = .248$	$F(2, 28) = 1.397$, $p = .264$, $n_p^2 = .091$	$F(2, 28) = .760$, $p = .477$, $n_p^2 = .051$

Table 2. Results from the 3 (model condition) x 2 (before and after observation) mixed model ANOVA for accuracy performance. The between subjects variable is the model condition and the within subjects variable is the accuracy in dart throwing performance before and after observation.

A mixed model ANOVA on dart throwing accuracy performance (see Table 2 above) revealed a main effect of time (from before to after observation) ($F(1, 28) = 9.228$, $p = .005$, $n_p^2 = .248$). Overall, participants were more accurate in the test phase (after the observation phase) compared to the familiarization phase (before observation). No other main effects or interactions were significant ($p > .05$). Although participants' accuracy improved after the observation phase, that improvement does not appear to depend on the model that participants observed. Instead, it seems reasonable to conclude that increased dart throwing performance may have simply resulted from physical practice effects.

Table 3 shows the results of the mixed model ANOVA for precision in dart throwing performance which revealed a significant main effect of time (F (1, 28) = 8.906, $p = .006$, n_p^2 = .241) such that precision for all participants was greater after the observation period than before. However, there was no main effect of the model condition nor was there a significant interaction between time and model condition (both $p > .05$). These results suggest that more physical practice can improve motor skill acquisition but that the observation of different dart throwing models did not guide this improvement in precision.

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Interaction of Time * Group**
F-test on Precision	F(1, 28) = 8.906, $\boldsymbol{p}$ **= .006**, n_p^2 = .241	F(2, 28) = .862, $p = .433$, n_p^2 = .058	F(2, 28) = 1.735, $p = .195$, n_p^2 = .110

Table 3. Results from the 3 (model condition) x 2 (before and after performance) mixed model ANOVA for dart throwing precision. The between subjects variable is the model condition and the within subjects variable is dart throwing precision before and after observation.

The results of the mixed model ANOVA on the average number of misses from before to after the observation phase by model condition group can be seen in Table 4. The main effects for time and model condition were not significant ($p > .05$). However, there was a significant interaction between time and video condition group (F (2, 28) = 3.888, $p = .032$, n_p^2 = .217). Post hoc tests did not reveal any significant differences between the average number of misses across the three model conditions (all $p > .05$). Figure 4 shows the average number of misses by each group both before and after the observation period.

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Interaction of Time * Group
F-test on Misses	F(1, 28) = 1.723, p = .200, n_p^2 = .058	F(2, 28) = 1.169, p = .325, n_p^2 = .077	F(2, 28) = 3.888, ***p* = .032**, n_p^2 = .217

Table 4. Results from the 3 (model condition) x 2 (before and after performance) mixed model ANOVA for dart throwing misses. The between subjects variable is the model condition and the within subjects variable is the average number of misses before and after observation.

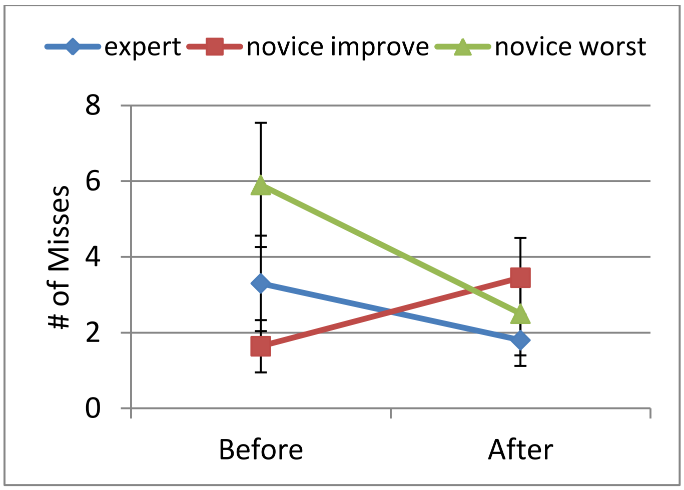


Figure 5. The average number of misses before and after observation by model condition.

As can be seen in Figure 5, the number of missed dart throws decreased after the observation phase for participants in the expert and novice worst conditions. On the other hand, participants in the novice improve video condition missed more dart throws after the observation period. While these such differences amongst the video groups likely drove the significant interaction, the average number of misses overall were relatively small and the data for misses need to be interpreted cautiously as there was a marginally significant difference between the novice improve video group and the novice worst model group before the observation period.

Finally, a mixed model ANOVA on the average number of bounces from before to after the observation phase by model condition group confirmed no main effect of time, no main effect of video condition group, and no interaction (all p > .05, see Table 5). While the interaction of time and video condition group trended towards significance, the overall frequency of bounces was even more rare than the frequency of misses (see Table 1). Therefore, any in-depth interpretation would not be informative.

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Interaction of Time * Group**
F-test on Bounces	$F(1, 28) = 2.667$, $p = .114$, $n_p^2 = .087$	$F(2, 28) = .594$, $p = .559$, $n_p^2 = .041$	$F(2, 28) = 2.628$, $p = .090$, $n_p^2 = .158$

Table 5. Results from the 3 (model condition) x 2 (before and after video observation) mixed model ANOVA for the average number of bounces. The between subjects variable is the video condition and the within subjects variable is the average number of bounces before and after model observation.

Individual differences in dart throwing performance. While all of the participants were novices in dart throwing, it is possible that that some participants were simply better overall athletes. To determine if general athletic abilities, rather than dart throwing expertise per se, influenced dart throwing performance, the total participant pool was broken up into quartiles based on their accuracy and precision performance in the familiarization phase. The participants who performed best initially were then compared to the participants who performed worst initially in a 3 (model condition) x 2 (top and bottom quartiles) x 2 (before and after performance) mixed model ANOVA for accuracy, precision, misses, and bounces. By only examining participants in the top and bottom quartiles, these analyses only included data from eight participants in the top quartile (n = 4 expert video condition, n = 2 novice improve video condition, n = 2 novice worst video condition) and nine participants in the bottom quartile (n = 3 expert video condition, n = 3 novice improve video condition, n = 3 novice worst video condition). The results of the mixed model ANOVA for accuracy are shown in Table 6 below.

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Main Effect of Quartile	Interaction of Time * Group	Interaction of Time * Quartile	3 way interaction Time* Group* Quartile
F-test on Accuracy	$F(1, 11) = 4.990$, $\mathbf{p = .047}$, $n_p^2 = .312$	$F(2, 11) = 1.816$, $p = .208$, $n_p^2 = .248$	$F(1, 11) = 53.582$, $\mathbf{p = .000}$, $n_p^2 = .830$	$F(2, 11) = .458$, $p = .644$, $n_p^2 = .077$	$F(1, 11) = .048$, $p = .830$, $n_p^2 = .004$	$F(2, 11) = 1.479$, $p = .270$, $n_p^2 = .212$

Table 6. Results from the 3 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for accuracy performance. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the accuracy performance before and after observation.

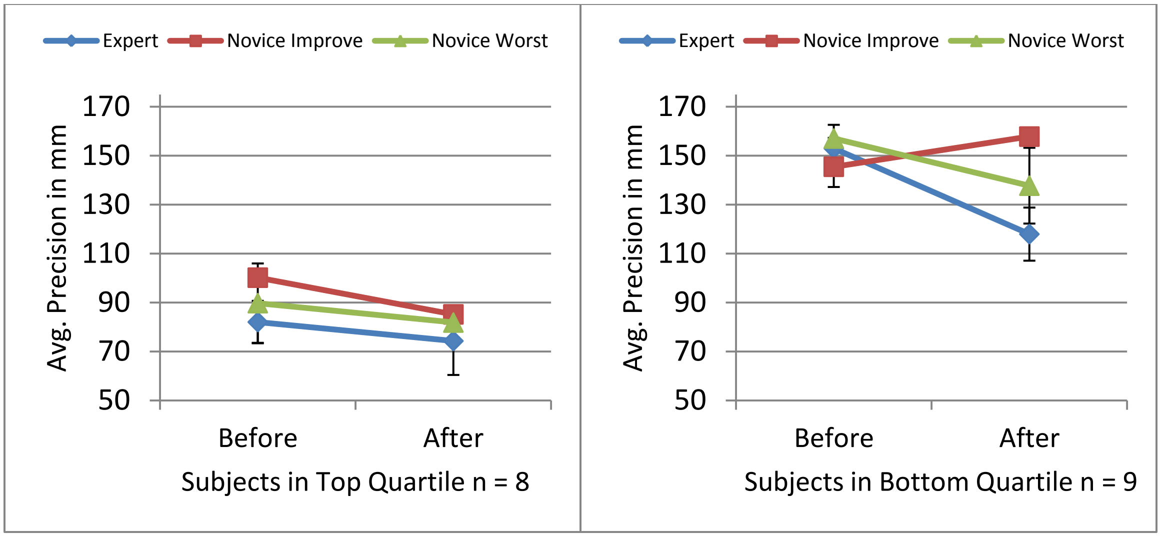
The results showed a significant main effect of time such that performance accuracy improved after observation overall for both the top and bottom performing participants ($F(1, 11) = 4.990$, $p = .047$, $n_p^2 = .312$). Furthermore, there was a significant main effect of quartile such that participants in the top quartile performed more accurately overall than participants in the bottom quartile ($F(1, 11) = 53.582$, $p = .000$, $n_p^2 = .830$). The significant main effect for quartile is not surprising as the participants included in this analysis were specifically selected for their superior or poor performance in the familiarization phase. No other main effects or interactions reached significance ($p > .05$).

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Main Effect of Quartile	Interaction of Time * Group	Interaction of Time * Quartile	3 way interaction Time* Group* Quartile
F-test on Precision	$F(1, 11) = 8.339$, $\mathbf{p = .015}$, $n_p^2 = .431$	$F(2, 11) = 1.592$, $p = .247$, $n_p^2 = .224$	$F(1, 11) = 63.547$, $\mathbf{p = .000}$, $n_p^2 = .852$	$F(2, 11) = 2.018$, $p = .179$, $n_p^2 = .268$	$F(1, 11) = .203$, $p = .661$, $n_p^2 = .018$	$F(2, 11) = 3.809$, $\mathbf{p = .055}$, $n_p^2 = .409$

Table 7. Results from 3 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for precision performance. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the precision performance before and after observation.

The results of the mixed model ANOVA for precision are shown above in Table 7. Again, there was a significant main effect of time (F (1, 11) = 8.339, p = .015, n_p^2 = .431) and a main effect of quartile (F (1, 11) = 63.547, p = .000, n_p^2 = .852). Interestingly, there was a marginally significant three-way interaction between time, model condition group, and quartile (F (2, 11) = 3.809, p = .055, n_p^2 = 409). Figures 6 and 7 depict the average precision before and after observation by model condition group for the participants in the top quartile (Figure 6) and participants in the bottom quartile (Figure 7). Participants in the top quartile show an overall improvement in precision from before to after observation in all of the model conditions. The participants in the bottom quartile, however, demonstrate a slightly different pattern of results. Surprisingly, participants in the bottom quartile who viewed the novice improve video actually performed worse after the observation phase. To determine if any of these differences were significant, one-way ANOVAs were conducted on: 1) top quartile participants before observation comparing the model condition groups, 2) bottom quartile participants before observation comparing model condition groups, 3) top quartile participants after observation comparing the model condition groups, and 4) bottom quartile participants before observation comparing model condition groups.

Before the observation phase, there were no significant differences between the video conditions for participants in either the top quartile (F (2, 5) = .949, p = .447, n_p^2 = .275) or the bottom quartile (F (2, 6) = .869, p = .466, n_p^2 = .225). After the observation phase, there were no significant differences between the performances of the three experimental groups in the top quartile (F (2, 5) = .193, p = .831, n_p^2 = .072). In the bottom quartile, there was a trend towards significance such that the participants in the expert video condition performed marginally better than participants in the novice improve condition (F (2, 5) = 3.245, p = .096, n_p^2 = .520). This difference in participants in the bottom quartile after observation is likely driving the marginally significant three-way interaction for precision.



Figures 6 and 7. Precision before and after the observation phase by model condition group for top performing participants (Figure 6 on left) and worst performing participants (Figure 7 on right).

The results for the 3 x 2 x 2 mixed model ANOVA for misses are shown in Table 8. There was a significant main effect of video condition group (F (2, 11) = 5.823, p = .019, n_p^2 = .515) and main effect of quartile (F (1, 11) = 25.820, p = .000, n_p^2 = .701). Furthermore, there was a marginally significant interaction between the average number of misses from before to after the observation phase by video condition group (F (2, 11) = 3.059, p = .088, n_p^2 = .357). None of the other main effects or interactions reached significance (all p > .05).

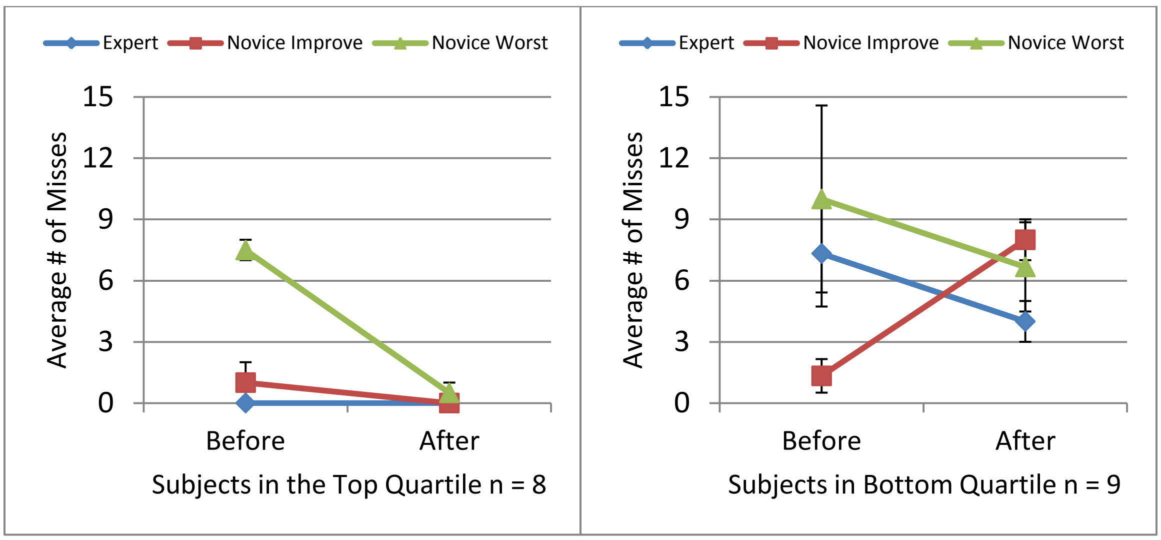
	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Main Effect of Quartile**	**Interaction of Time * Group**	**Interaction of Time * Quartile**	**3 way interaction Time* Group* Quartile**
F-test on Misses	F(1, 11) = 1.125, p = .311, n_p^2 = .093	F(2, 11) = 5.823, ***p* = .019,** n_p^2 = .515	F(1, 11) = 25.820, ***p* = .000 ,** n_p^2 = .701	F(2, 11) = 3.059, ***p* = .088,** n_p^2 = .357	F(1, 11) = 1.125, p = .311, n_p^2 = .093	F(2, 11) = 1.792, p = .212, n_p^2 = .246

Table 8. Results from 3 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for misses. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the precision performance before and after observation.

While the main effect of quartile is unsurprising, the main effect for model condition and the interaction of time and model type required further investigation. Post hoc tests for the main effect of experimental group showed that participants in the novice worst video condition threw more misses overall than participants in the expert video condition (F (2,11) = 5.823, p = .035) and participants in the novice improve video condition (F (2, 11) = 5.823, p = .037). For the marginally significant interaction, participants in the top and bottom quartile and who viewed the novice worst video performed significantly worse overall than those who viewed the expert video (F (2, 11) = 5.823, p = .007) and who viewed the novice improve video (F (2, 11) = 5.823, p = .027).

For the marginally significant interaction of time and group, Figures 8 and 9 depict the average number of misses from before and after the observation phase by model condition for participants in the top quartile (Figure 8) and in the bottom quartile (Figure 9). From these graphs, it is apparent that participants in the top quartile overall threw fewer misses than participants in the bottom quartile. Top performing participants in the expert video and novice improve video conditions showed little improvement after the observation phase due to the fact that these participants never missed or rarely missed. Participants in the top quartile and who also viewed the novice worst video showed a large improvement from before to after the observation phase.

In the bottom quartile, participants who observed the expert or the novice worst videos threw fewer misses after the observation phase. However, participants who viewed the novice improve video and were in the bottom quartile threw more misses after the observation phase. To determine if any of these differences are significant, one-way ANOVAs were conducted on: 1) top quartile participants before observation comparing the model condition groups, 2) bottom quartile participants before observation comparing model condition groups, 3) top quartile participants after observation comparing the model condition groups, and 4) bottom quartile participants before observation comparing model condition groups. Before the observation phase, there was a significant difference between the model conditions groups for the average number of misses in the top quartile ($F(2, 5) = 78.375$, $p = .000$, $n_p^2 = .969$). Post hoc revealed that participants in the novice worst condition performed significantly worse than participants in the expert video condition ($F(2, 5) = 78.375$, $p < .000$) and participants in the novice improve video condition ($F(2, 5) = 78.375$, $p = .001$). There were no differences by video condition for misses in the bottom quartile ($F(2, 6) = 2.070$, $p = .207$, $n_p^2 = .408$). Also, there were no significant differences between the video groups after the observation phase in either the top quartile participants ($F(2, 5) = 1.875$, $p = .247$, $n_p^2 = .429$) or the bottom quartile participants ($F(2, 6) = 1.836$, $p = .239$, $n_p^2 = .380$).



Figures 8 and 9. The average number of misses before and after the observation phase by model condition for the top performing participants (Figure 8 on left) and the worst performing participants (Figure 9 on right).

The results for the 3 x 2 x 2 mixed model ANOVA for bounces are not shown because there were no significant main effects or interactions (all $p > .05$).

Improvement of dart throwing over time. Comparing aggregate accuracy, precision, misses, and bounces scores from before to after the observation phase can be informative on the effects of the model condition participants observed, but this measure may not fully capture change in these outcome measures over time. Difference scores capture continuous performance change from the first sets of dart throws to the last sets of dart throws across the video condition groups. Both before and after observation, participants threw a total of 25 sets of 3 darts. To create difference scores, performance in the 25 sets of dart throws before observation and performance in the 25 sets of dart throws after observation were first combined into phases (see Table 9). A phase consisted of the performance of five sets of dart throws. Phases 1 – 5 represent participants' performance before the observation of a model, while Phases 6 – 10 represent participants' performance after the observation phase.

Phase	Definition
Phase 1	Dart throwing performance in Sets 1 – 5 (before observation)
Phase 2	Dart throwing performance in Sets 6 – 10 (before observation)
Phase 3	Dart throwing performance in Sets 11 – 15 (before observation)
Phase 4	Dart throwing performance in Sets 16 - 20 (before observation)
Phase 5	Dart throwing performance in Sets 21 - 25 (before observation)
Phase 6	Dart throwing performance in Sets 1 – 5 (after observation)
Phase 7	Dart throwing performance in Sets 6 - 10 (after observation)
Phase 8	Dart throwing performance in Sets 11 - 15 (after observation)
Phase 9	Dart throwing performance in Sets 16 - 20 (after observation)
Phase 10	Dart throwing performance in Sets 21 - 25 (after observation)

Table 9. Description of phase data by dart throwing sets. Each phase consists of five sets of darts (or 15 individual dart throws). Phase data were plotted for accuracy and precision performance by video condition.

Figures 10 and 11 illustrate the average accuracy of each video group (Figure 10) and the average precision of each model condition (Figure 11) plotted into phases.

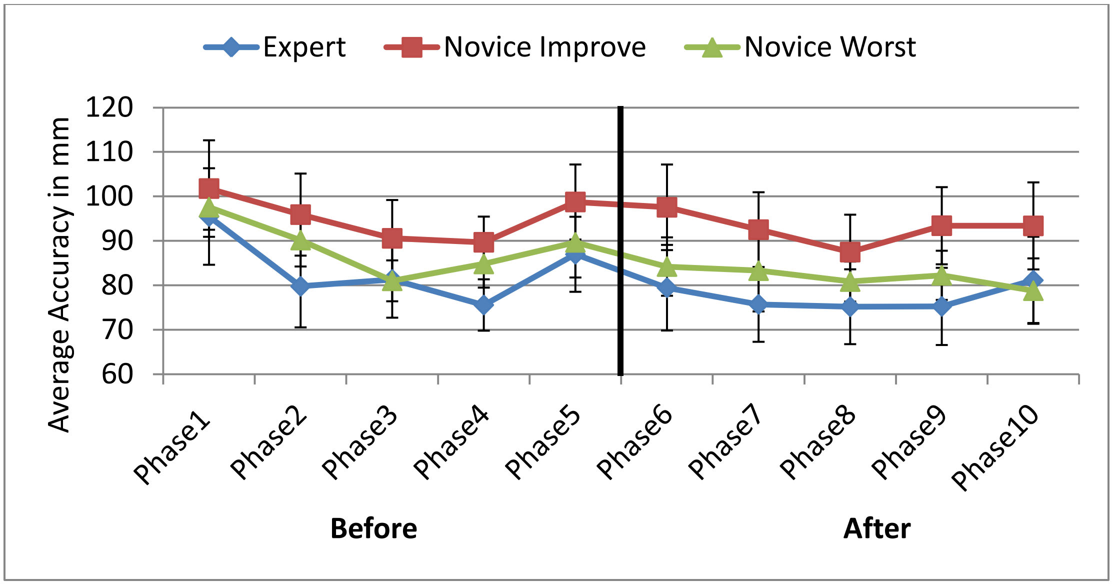


Figure 10. The average accuracy by model condition for Phases 1 – 5 before observation and Phases 6 – 10 after observation. The vertical black line between Phases 5 and 6 represents the observation period.

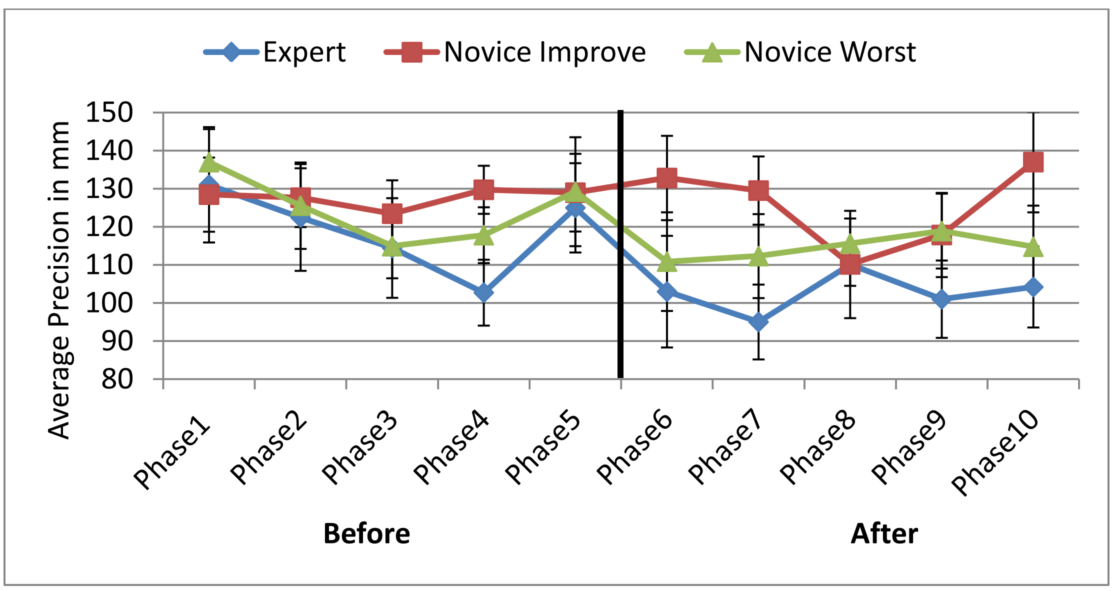


Figure 11. The average precision by model condition for Phases 1 – 5 before observation and Phases 6 – 10 after observation. The vertical black line between Phases 5 and 6 represents the observation period.

Using the average accuracy and precision scores for each experimental group in each phase, difference scores before the observation phase were calculated by subtracting the average scores in Phase 1 from Phase 5 (Phase 5 – Phase 1). A negative score would indicate that on average participants' performance improved from Phase 1 to Phase 5. A positive score, on the other hand, would indicate a decline in performance from Phase 1 to Phase 5. The calculated difference scores from before observation can be seen in Table 10 below.

Model Condition	**Accuracy Difference Score Before**	**Precision Difference Score Before**
	(Phase 5 – Phase 1)	*(Phase 5 – Phase 1)*
Expert Video	-8.498 (SE = 4.89)	-6.050 (SE = 13.62)
Novice Improve Video	-3.022 (SE = 7.95)	.518 (SE = 12.73)
Novice Worst Video	-7.907 (SE = 4.04)	-7.749 (SE = 13.50)

Table 10. Accuracy and spread difference scores from before observation calculated by subtracting the average accuracy and precision score for each experimental group in Phase 1 from the average accuracy and precision scores for each group in Phase 5.

Before the observation phase, participants in the expert video condition and in the novice worst video condition improved both in accuracy and precision from Phase 1 to Phase 5. The participants in the novice improve video condition also were more accurate from Phase 1 to Phase 5, however, they performed slightly worse from Phase 1 to Phase 5 in terms of precision. A one-way ANOVA for accuracy difference scores and precision difference scores revealed that there were no significant differences in the accuracy difference scores by video group ($F(2, 28) = .254$, $p = .777$, $n_p^2 = .018$) and no significant differences in the precision difference scores by video group ($F(2, 28) = .111$, $p = .895$, $n_p^2 = .008$). This suggests that the rate of change in dart throwing performance was similar across the participants in the different video condition groups before the observation phase.

Difference scores were also calculated for accuracy and precision after the observation phase by subtracting the average scores in Phase 6 from the average scores in Phase 10 (Phase 10 – Phase 6) for each experimental group. In this case, we should expect that if the model condition had an effect on the subsequent dart throwing performance that there would be differences between the model conditions. The calculated difference scores from after observation of the models can be seen in Table 11 below.

Model Condition	**Accuracy Difference Score After**	**Precision Difference Score After**
	(Phase 10 – Phase 6)	*(Phase 10 – Phase 6)*
Expert Video	1.672 (SE = 7.63)	1.212 (SE = 6.43)
Novice Improve Video	- 4.180 (SE = 5.13)	4.172 (SE = 11.08)
Novice Worst Video	5.434 (SE = 7.18)	3.900 (SE = 15.58)

Table 11. Accuracy and spread difference scores from after observation calculated by subtracting the average accuracy and precision score for each experimental group in Phase 6 from the average accuracy and precision scores for each group in Phase 10.

Surprisingly, after the observation phase, all three experimental groups of the performed slightly worse from Phase 6 to Phase 10 with the exception of the accuracy difference score for the participants in the novice improve video condition. A one-way ANOVA demonstrated that the accuracy difference scores across groups are not significantly different (F (2, 28) = .318, p = .730, n_p^2 = .022) and that the precision difference scores across groups are not significantly different (F (2, 28) = .020, p = .981, n_p^2 = .001). Against our expectations, there were no differences in accuracy or precision between the video conditions. Furthermore, the participants in expert video condition and in the novice worst video condition showed slight improvement before observation but showed a decline in performance after observation in both accuracy and precision. Participants in the novice improve video condition showed slight improvement in accuracy both before and after observation but for precision only showed a decline in performance both before and after observation.

A closer look at Figures 10 and 11, and specifically in Phase 5 and in Phase 10, shows that it is possible that participants were simply fatigued by these points in the experiment (throwing a dart 75 times is quite taxing). It appears that overall participants are improving until the very last phase (Phase 5 and Phase 10). By calculating difference scores using Phase 5 and Phase 10, this may be adding additional noise into the data set. In light of this, accuracy and precision difference scores were calculated again but used Phase 4 and Phase 9 instead. Before observation, the difference scores deduct the average accuracy and precision scores in Phase1 from Phase 4 (Phase 4 – Phase 1) for each of the video conditions. After observation, the difference scores deduct the average accuracy and precision scores in Phase 6 from Phase 9 (Phase 9 – Phase 6). The calculated difference scores from before and after observation by model condition group are in Table 12.

Despite the seemingly dramatic disparity in the calculated difference scores from (Phase 5 – Phase 1) and (Phase 10 – Phase 6) to (Phase 4 – Phase 1) and (Phase 9 – Phase 6), one-way ANOVAs revealed no significant differences between the video conditions on accuracy difference scores before observation (F (2, 28) = 2.049, p = .148, n_p^2 = .033) or after observation (F (2, 28) = .045, p = .956, n_p^2 = .003) and no significant differences on precision difference scores before observation (F (2, 28) = .483, p = .622, n_p^2 = .128) or after observation (F (2, 28) = 1.281, p = .294, n_p^2 = .084).

Model Condition	Accuracy Difference Score Before	Precision Difference Score Before
	(Phase 4 – Phase 1)	*(Phase 4 – Phase 1)*
Expert Video	-19.964 (SE = 6.72)	-28.320 (SE = 10.63)
Novice Improve Video	-12.089 (SE = 7.27)	1.276 (SE = 12.26)
Novice Worst Video	-12.770 (SE = 3.93)	-19.168 (SE = 8.51)

Model Condition	Accuracy Difference Score After	Precision Difference Score After
	(Phase 9 – Phase 6)	*(Phase 9 – Phase 6)*
Expert Video	-4.207 (SE = 7.94)	-1.973 (SE = 6.43)
Novice Improve Video	-4.138 (SE = 13.04)	-14.967 (SE = 6.46)
Novice Worst Video	-1.967 (SE = 8.28)	8.013 (SE = 4.70)

Table 12. Accuracy and spread difference scores from before observation calculated by subtracting the average accuracy and precision score for each experimental group in Phase 1 from the average accuracy and precision scores for each group in Phase 4. Accuracy and spread difference scores from after observation calculated by subtracting the average accuracy and precision score for each video group in Phase 6 from the average accuracy and precision score for each group in Phase 9.

The rate of improvement for participants in the expert video condition was much larger before the observation phase as compared to after the observation phase. Similarly, for participants in the novice improve and novice worst video conditions, the accuracy difference scores indicated a bigger improvement before the observation phase as compared to after. The precision difference scores illustrate that participants in the novice worst video condition demonstrated precision improvement before the observation phase but a decline in precision after the observation phase. Conversely, participants in the novice improve video condition demonstrated a slight decline in precision before the observation phase but an improvement in precision after observation.

Lastly, a final set of difference scores were calculated for accuracy and precision. It may be the case that one phase (five sets of darts) is too little information to capture the change in performance over time. In this final set of difference scores, accuracy and precision difference scores were calculated as the following:

- Before observation: (Average scores of Phases 3 and 4) – (Average scores of Phases1 and 2)
- After observation: (Average scores of Phases 8 and 9) – (Average scores of Phases 6 and 7)

These final difference scores are displayed in Table 13.

Model Condition	**Accuracy Difference Score Before**	**Precision Difference Score Before**
	(Phase 3&4 – Phase 1&2)	*(Phase 3&4 – Phase 1&2)*
Expert Video	-9.204 (SE = 5.04)	-48.310 (SE = 9.35)
Novice Improve Video	-8.717 (SE = 5.30)	-37.913 (SE = 4.63)
Novice Worst Video	-10.970 (SE = 2.52)	-48.334 (SE = 4.77)

Model Condition	**Accuracy Difference Score After**	**Precision Difference Score After**
	(Phase 6&7 – Phase 8&9)	*(Phase 6&7 – Phase 8&9)*
Expert Video	-2.368 (SE = 4.83)	6.563 (SE = 6.48)
Novice Improve Video	-4.597 (SE = 4.52)	-17.170 (SE = 9.08)
Novice Worst Video	-2.212 (SE = 3.92)	5.656 (SE = 4.36)

Table 13. Accuracy and spread difference scores from before observation calculated by subtracting the average accuracy and precision score for each experimental group in Phases 1 and 2 from the average accuracy and precision scores for each group in Phases 3 and 4. Accuracy and spread difference scores from after observation calculated by subtracting the average accuracy and precision score for each video group in Phases 6 and 7 from the average accuracy and precision score for each group in Phases 8 and 9.

Before the observation phase, one way ANOVAs established no statistically significant differences in accuracy difference scores (F (2, 28) = .068, p = .934, n_p^2 = .005) or in precision difference scores (F (2, 28) = .877, p = .427, n_p^2 = .059). After the observation phase, there was no significant difference between the video conditions on accuracy differences scores (F (2, 28) = .092, p = .912, n_p^2 = .007). There was a significant difference in the precision scores after observation (F (2, 28) = 3.704, p = .037, n_p^2 = .209). According to post hoc tests, participants in the novice improve video condition performed marginally better than participants in the expert video condition (F (2, 28) = 3.704, *p* = .061) and participants in the novice worst video condition (F (2, 28) = 3.704, *p* = .074) after the observation phase.

2.1.4 Discussion.

Two theories of action understanding have been posited here as potential explanations for the phenomenon of observational learning. First, the direct matching theory of action understanding (Rizzolatti et al., 2001; Rizzolatti & Craighero, 2004) has been supported through neurological and psychophysical evidence of coupled visual and motor processing. On the neurophysiological level, areas of the human brain that are involved in action execution also appear to contribute to action observation (e.g., Iacoboni, 1999; Kilner et al., 2009). On the psychophysical level, action production has been shown to systematically influence action perception (e.g., Prinz, 1997; Reed & Farah, 1995; Jacobs & Shiffrar, 2005). Direct matching is thought to be a bottom-up process in which observed actions are visually represented at the kinematic level and then matched to motor representations in the observer in a one-to-one fashion (Rizzolatti et al, 2001). The higher representation of the action goal is triggered by this bottom-up, one-to-one matching process such that the action can be understood.

One major criticism of the direct matching theory is that actions with similar kinematics may result in different action goals (Zentgraf et al., 2011). As an example, imagine observing someone reach out and pick up a cup. The kinematic information of this action would be the same regardless of whether this person intended to take a drink from the cup or to hand the cup to another person. The direct matching theory has difficulty explaining this. A second theory of action understanding, on the other hand, can explain this discrepancy. The action reconstruction theory (Csibra, 2008) suggests that observing a model perform an action first activates the higher-level goal representation and then the observer can "reconstruct" an action pattern to achieve this goal. This can be understood as a kind of reverse engineering. The resulting action executed by the observer could match the same kinematics as the model or use different kinematics.

As these theories related to Experiment 1, the direct matching theory (Rizzolatti, et al., 2001) would predict the novice participants should be best able to directly match the actions of a novice model as both the participants and the model are at the same skill level. Although two videos used in the observation phase of Experiment 1 featured a novice model, only the novice improve video (in which the model improved both in accuracy and precision) would be informative to the novice participants. This is a key distinction from previous work on observational learning and model expertise (see Rohnbadfard & Proteau, 2011). On the other hand, novice participants observing the expert dart throwing model could not directly match the observed dart throwing skills to their own motor repertoire as these skills do not exist yet. Improvement on the part of the participants, then, relies on extracting motor information from the expert model on performing the dart throwing skills accurately and precisely, as would be predicted by the action reconstruction theory (Csibra, 2008). As described below, the data from this experiment, unfortunately, do not unambiguously support either theory of observational learning.

Coinciding with the direct matching theory, observing a novice learning to perform a novel motor skill has been shown to produce observational learning effects in multiple studies (Blandin et al., 1999; Buchanan et al., 2008; Mattar & Gribble, 2005; Brown et al., 2009). In Experiment 1, participants who observed a novice model improve at dart throwing over the course of the observation phase demonstrated the greatest improvement in precision when measured on a continuous scale. This is in line with previous observational learning studies with novice models. However, in all of the additional analyses, participants who viewed the novice improve video demonstrated no other improvements above and beyond that of the other model conditions. This lack of convergent patterns of results frustrates the ability to draw clear conclusions.

Observational learning effects have been demonstrated previously with expert models, in line with the action reconstruction theory (Heyes & Foster, 2002; Bird & Heyes, 2005; Al-Abood et al., 2001). The results from Experiment 1 lend weak support for superior observation learning from the expert dart throwing model. All of the participants' accuracy performance improved from before to after the observation phase, regardless of the model type. Furthermore, all of the participants in the three model conditions demonstrated similar rates of continuous change in dart throwing accuracy over the course of the experiment. It was only when examining performance precision of the participants who were the best performers compared to participants who were the worst performers at the start of the experiment that some support for the benefits of the expert model was revealed. Participants in the bottom quartile and who observed the novice improve video performed less precisely after the observation phase than before. Furthermore, the average precision of bottom quartile participants in the novice improve model condition was marginally worse than the average precision of participants in the bottom quartile and who viewed the expert model. This could be taken to partially support the action reconstruction theory, however, it is important to note that participants in the bottom quartile and viewed the novice worst model performed no differently than those viewing the expert model.

Although the results do not overwhelmingly support either the direct matching or action reconstruction theories, Experiment 1 extends previous research on observational learning through the addition of a key control condition. One group of participants in Experiment 1 observed a novice model who did not demonstrate learning of or improvement in his dart throwing actions. While Rohnbadfard and Proteau (2011) did examine whether observing an expert or novice model is more beneficial to observational learning, they did not test whether observing a model performing the to-be-learned task inconsistently is influential on observer's subsequent performance. Overall, participants in Experiment 1 who viewed a model void of any useful information on improving one's own dart throwing skills (novice worst model condition) showed similar improvements in motor performance to participants in the other conditions. One explanation for this is that participants' improvements in dart throwing were simply due to physical practice during the course of the experiment. An alternative explanation is that observing a model's consistent performance of the to-be-learned task, whether the performance is superior or poor, is informative to observers. It may be the case that observing a model throw darts consistently well or consistently poorly is more predictable and thus easier to extract kinematic information from.

Limitations. Experiment 1 had several weaknesses that will be addressed in Experiment 2. First, only 31 participants participated in this study and thus there were only 10 – 11 participants in each of the 3 model conditions. Further, the variability in the overall performance of the participants was rather high, so with a small sample size and high variability, potential findings are tough to detect. In Experiment 2 described below, each of the video conditions included at least 25 participants' data. The inclusion of more participants boosts statistical power needed to further determine if the experimental manipulations are effective or if the effect in fact does not exist in our paradigm. Secondly, when the accuracy and precision data were plotted out over time in phases, instead of aggregated before and after video observation, the data suggested that participants may have become fatigued during the experiment. While overall there was improvement in the accuracy and precision of the novice participants' dart throwing from Phase 1 to Phase 4 and from Phase 6 to Phase 9, when the data were analyzed to include the last sets of dart throws (i.e., Phases 5 and 10), performance declined. Participant fatigue may have attenuated learning effects. Therefore, in Experiment 2, the number of dart throws was reduced from 25 sets to 15 sets both before and after the observation phase. Finally, Experiment 2 was constructed so as to address the possibility of the results in Experiment 1 emerging from physical practice alone. All of the participants in Experiment 1 observed dart throwing, whether by an expert or novice model.

Initially, the novice worst model condition was considered as a control condition, but it is possible that seeing any consistent dart throwing performance is informative. To account for this possibility, Experiment 2 included a fourth video condition featuring a model shooting Nerf basketball. While this model displays expert basketball shooting, but this action differs significantly from dart throwing. Thus, the addition of this condition allowed for the comparison of observational learning while watching actions that are very similar to, or different from, the action that the observer attempts to perform.

2.2 Experiment 2: Observational Learning with a Motor Relevant or Irrelevant Model

2.2.1 Hypothesis and theoretical motivation.

To what extent did the ambiguous results from Experiment 1 result from the particular methodological conditions employed? To answer this question, Experiment 2 was to improve upon Experiment 1 in the following ways. First, more participants were included to boost the power of the subsequent analyses. Second, the sets of darts thrown before and after observation were reduced from 25 sets to 15 sets to prevent fatigue. Finally, a new control condition was created to disentangle the effects of physical practice from the effects of the dart throwing model observation.

The results from Experiment 1 were not conclusive about whether participants used a direct matching or action reconstruction process during observational learning. The only statistically significant differences amongst the experimental groups surfaced when examining dart throwing precision. Participants in the novice improve video condition demonstrated the greatest improvement after the observation phase for continuously measured precision. However, the worst performing participants in the expert and novice worst video conditions improved in terms of precision when examining aggregate precision scores before and after the observation phase.

One potential explanation for the results of Experiment 1 is simply that the effects may have been due to physical practice. However, an alternative explanation is that the observation of any kind of dart throwing is sufficient to help observers learn how to throw darts. Indeed, the results of Experiment 1 can be seen as consistent with those of Rohnbadfard and Proteau (2011) in that these researchers similarly did not observe large differences in participants' performance following the observation of the expert model as compared to the novice model performing the to-be-learned task. To address this possibility, a key control video condition was added to the current study. The control video featured a model performing an action other than dart throwing; namely, shooting Nerf basketballs into a hoop very accurately and precisely. First, basketball was chosen as a control condition as in previous research, visual sensitivity to basketball movements is related to motor experience with basketball (Sebanz & Shiffrar, 2009). Second, basketball, similar to dart throwing, is a goal-directed action that requires a pendular arm motion to throw the object towards the goal. Any improvement in dart throwing ability by participants in the basketball model condition can be attributed directly to physical practice. Indeed, since participants viewing the basketball video never observe a model throwing darts, any changes in their dart throwing cannot have arisen from the observation of dart throwing. If participants in the dart throwing model conditions do not differ from the basketball model condition in their dart throwing actions, then it could be concluded that all of the results in this and the previous study can be attributed to physical practice alone. However, if participants employ direct matching during observational learning, participants who observe the novice improve dart throwing model should show more improvement in their dart throws after the observation period than participants in the basketball model condition. On the other hand, if participants are reconstructing the observed action, the participants in the expert dart throwing model condition should perform better after the observation phase than participants in the basketball model condition.

2.2.2 Methods.

Participants. 101 Rutgers University – Newark undergraduate students (mean age = 20.37 years old; 43 males and 58 females) participated in the study for partial course credit. All of the participants had normal or corrected to normal vision and were dart throwing novices. The participants were all right handed throwers. The study was approved by the Rutgers University IRB and all participants provided written informed consent.

Materials. The materials for Experiment 2 were the same as the materials from Experiment 1. However, in addition to the three different dart throwing videos, there was an additional control video featuring Nerf basketball. In this video, the model (the expert dart throwing model from Experiment 1) threw a total of 76 successful baskets out of a total of 78 shots. This movie, like the movies in the other experimental conditions, lasted approximately four minutes long.

Model video construction. The basketball video, like the dart videos, was filmed with the same Canon HD VIXIA HF20 digital camera used in Experiment 1 from a 3/4 point of view that included the Nerf basketball, the model and the hoop all in the same shot. The raw video footage was captured in a single two hour session and was subsequently edited using Adobe Premiere Pro v2.0 down to 78 basketball shots. In the editing process, first, the successful basketball shots (going through the hoop) were identified. The video was then edited to include mostly successful shots and a couple missed shots. The model was featured in each individual shot segment as he picked up the ball and ended after the basketball went through the hoop. On the computer screen, the model measured 8.42 DVA in height and 8.53 DVA in width with the model's arm extended. This is slightly smaller than the visual angle for the dart throwing video conditions. The expert dart throwing video measured 9.65 DVA in height and 10.76 DVA in width, while the novice improve and novice worst dart throwing videos measured 10.43 DVA in height and 11.09 DVA in width.

Design and procedure. Participants were randomly assigned to one of four possible experimental video conditions in this between-subjects design. Participants were assigned to the expert video condition (n = 25), novice improve video condition (n = 27), novice worst video condition (n = 25), or basketball video condition (n = 26). As in Experiment 1, all of the participants performed the familiarization phase in which participants physically performed dart throwing, the observation phase in which participants observed a model throw darts or basketballs, and the test phase in which participants again physically threw darts. The procedure was the same as in Experiment 1 except that participants were asked to throw 15 sets of 3 darts (as opposed to 25 sets) at the archery target with the goal of throwing as many darts as possible into the yellow goal area in the familiarization and test phases (see Figure 12). One previous study showed that when athletic participants were purposefully fatigued, their decisions became quicker and more inaccurate during a speed discrimination task (Thomson et al., 2009). To avoid this potential problem, participants in Experiment 2 threw fewer darts than participants in Experiment 1.

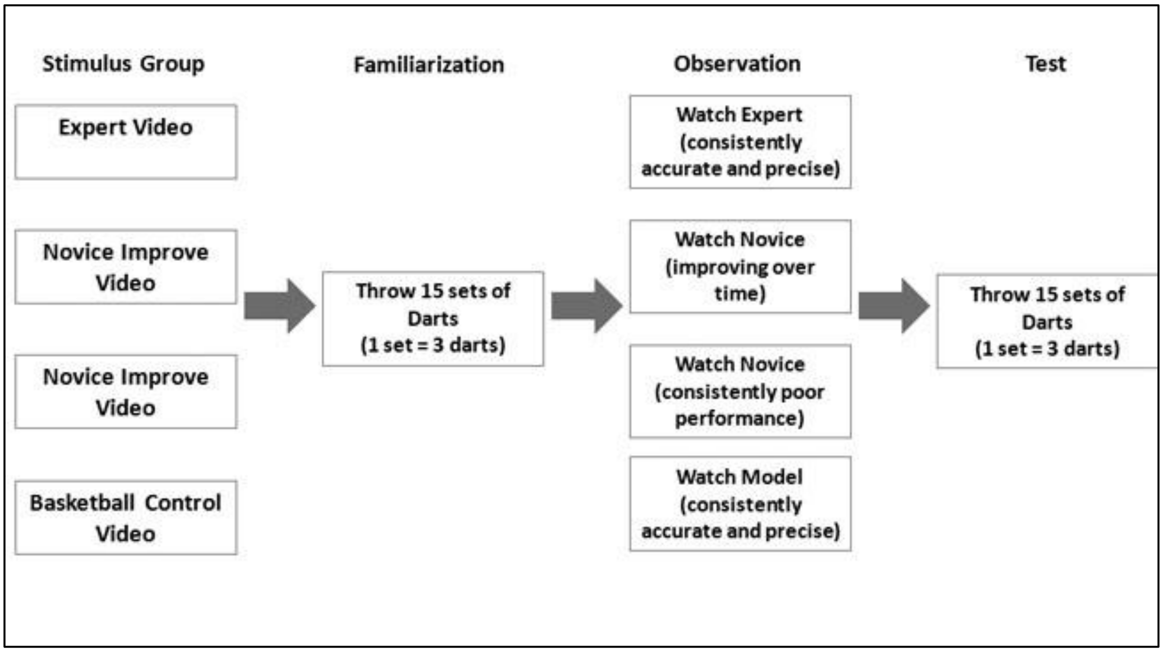


Figure 12. Experiment 2 design. Participants were randomly assigned to one of four different model conditions and completed the familiarization, observation, and test phases of the experiment.

Analyzing the target data. In Experiment 1, dart throwing accuracy and precision were measured by hand with a ruler. In Experiment 2, the landing locations of darts as well as the accuracy and precision of each set of dart throws were detected and computed with Matlab (The Mathworks Inc., Natick, US-MA). The participants' targets were photographed and imported into a custom written Matlab program that allowed us, by means of a graphical interface, to indicate the location of each dart's landing position. The Matlab program then took these positions, expressed as horizontal and vertical distances from the bull's eye, and used them to calculate the accuracy and precision of all dart throws.

First, accuracy for each individual participant was calculated by locating the centroid of all 15 sets of dart throws in the familiarization phase and similarly the centroid of all 15 sets of dart throws in the test phase. Accuracy for each participant was defined as the distance of the centroid to the bull's eye. These data were then averaged across the participants in each video condition for the familiarization phase and again for the test phase. Precision for each participant was defined as the average distance of each individual dart throw from the centroid. These data were averaged across all participants in each video condition from both before and after observation. Figure 13 illustrates the accuracy and precision analyses for Experiment 2.

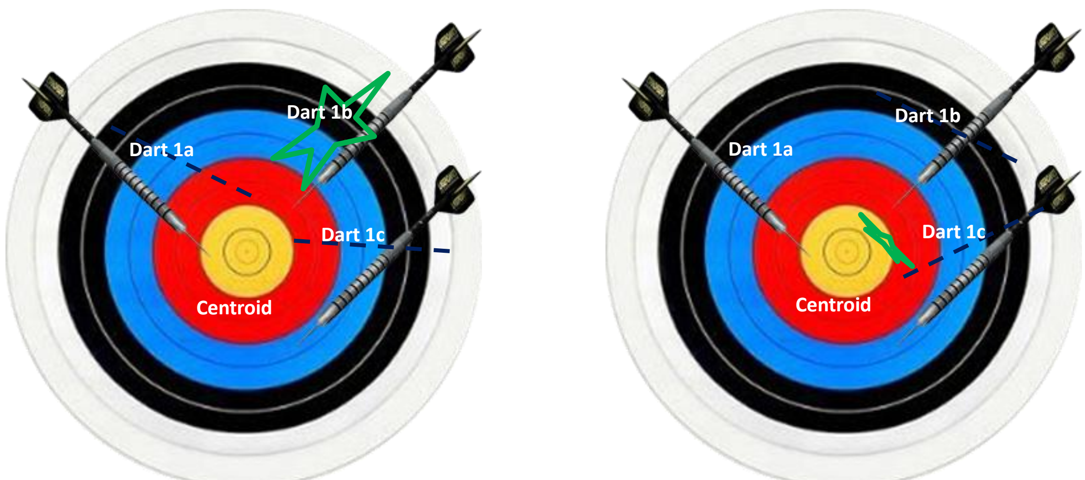


Figure 13. Illustrations of the measurement of accuracy (on left) and precision (on right) for Experiment 2. For each individual participant, accuracy was defined as distance from the centroid of all 15 sets of dart throws to the bull's eye. Precision was defined as average distance of each dart throw from the centroid.

As in Experiment 1, if participants observe the novice improve video and show better performance than the participants in the other dart throwing video conditions, then the data will support the direct matching hypothesis. Conversely, greater dart throwing improvement after the observation of the expert dart video would support the action reconstruction hypothesis. Further, it is expected that if observing any type of dart throwing is important to observational learning then participants in the basketball video condition should not improve their dart throws after video observation while participants in the dart throwing video conditions should improve.

2.2.3 Results.

After collection of the data, several outliers were identified (n = 15). An outlier was defined as performing a total of 17 errors (misses and bounces) from the familiarization phase and test phase. In Experiment 1, the percentage of errors that denoted two standard deviations above the mean was 18.92%. For Experiment 2, 18.92% of the total dart throws was approximately 17 dart throws. Thus, any participant who had 17 or more errors throughout the experiment was excluded in the analyses. This resulted in a total of 21 participants in the expert video condition, 21 in the novice improve video condition, 21 in the novice worst video condition, 23 in the control video condition. The results for the average accuracy (in mm), precision (in mm), and number of misses and bounces in the familiarization and test phases by experimental group can be seen in Table 14.

Video Condition	Accuracy Before	Accuracy After	Precision Before	Precision After	Misses Before	Misses After	Bounces Before	Bounces After
Expert Video	**31.00** (SE = 2.88)	**32.90** (SE = 2.78)	**88.39** (SE = 3.82)	**78.70** (SE = 2.81)	**2.71** (SE = .60)	**1.00** (SE = .32)	**.95** (SE = .28)	**.57** (SE = .11)
Novice Improve Video	**33.33** (SE = 4.00)	**30.19** (SE = 3.19)	**85.20** (SE = 3.79)	**84.22** (SE = 4.62)	**1.24** (SE = .33)	**1.67** (SE = .43)	**.81** (SE = .27)	**1.05** (SE = .31)
Novice Worst Video	**35.10** (SE = 3.43)	**31.03** (SE = 2.87)	**87.61** (SE = 2.65)	**82.00** (SE = 3.21)	**1.52** (SE = .38)	**1.25** (SE = .48)	**1.10** (SE = .24)	**.65** (SE = .22)
Basketball Video	**23.29** (SE = 2.49)	**26.17** (SE = 2.60)	**83.76** (SE = 2.95)	**83.49** (SE = 3.70)	**1.70** (SE = .36)	**1.13** (SE = .30)	**.65** (SE = .19)	**.65** (SE = .21)

Table 14. The average accuracy, precision, misses, and bounces before and after the observation of the four video conditions. Accuracy and precision are measured in millimeters. Misses and bounces are the average number of errors before and after the observation phase.

Familiarization phase. In order to conclude if participants in the four video conditions performed similarly in the familiarization phase (dart throwing before video observation), one-way ANOVAs were conducted on accuracy, precision, misses and bounces. The participants' performance did not differ across the four video conditions in terms of precision (F (3, 82) = .411, *p* = .745, n_p^2 = .015) or bounces (F (3, 82) = .595, *p* =.620, n_p^2 = .021). However, participants in the four video conditions did significantly differ in terms of their dart throwing accuracy before the video observation (F (3, 82) = 2.711, *p* =. 050, n_p^2 = .090). Post hoc tests revealed that participants in the basketball condition performed more accurately than participants in the novice worst video condition (F (3, 82) = 2.711, *p* = .050). Furthermore, a marginally significant difference was noted between the experimental groups for the average number of misses in the familiarization phase (F (3, 82) = 2.195, *p* = .095, n_p^2 = .074). Participants in the novice improve video condition threw fewer misses than participants in the expert video condition before the observation phase (F (3, 82) = 2.195, *p* = .084). While these differences should be noted, the purpose of the study is to determine changes in dart throwing performance from the familiarization phase (before observation) to the test phase (after observation). Nevertheless, the results for accuracy and misses should be interpreted with caution.

Dart throwing performance before and after model observation. Dart throwing performance before and after the observation phase was examined with a series of mixed model ANOVAs in which the between-subjects variable was the model condition and the within-subjects variable was dart throwing performance (accuracy, precision, misses and bounces) from before to after observation of the models. As a reminder, the lower score associated with the dart throwing performance measures indicates that participants were more accurate and precise in the physical performance of dart throwing. The results of the mixed model ANOVA for accuracy can be found in Table 15.

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Interaction of Time * Group
F-test on Accuracy	F(1, 82) = .152, *p* = .698, n_p^2 = .048	F(3, 82) = 2.208, ***p* = .093**, n_p^2 = .060	F(3, 82) = 1.283, *p* = .286, n_p^2 = .054

Table 15. Results from the 4 (model condition) x 2 (before and after performance) mixed model ANOVA for accuracy performance. The between subjects variable is the model condition and the within subjects variable is the accuracy of dart throwing performance before and after observation.

For the average accuracy, the mixed model ANOVA revealed a marginally significant main effect of model condition (F (3, 82) = 2.208, *p* = .093, n_p^2 = .060). The post hoc tests indicated a marginally significant difference between the average accuracy of participants in the novice worst model condition and participants in the basketball model control condition (F (3, 82) = 2.208, *p* = .112). As can be seen in Figure 14, participants in the basketball model condition performed more accurately overall in both before and after the observation phase than participants in the novice worst model condition. There were no other significant main effects or interactions (*p* > .05).

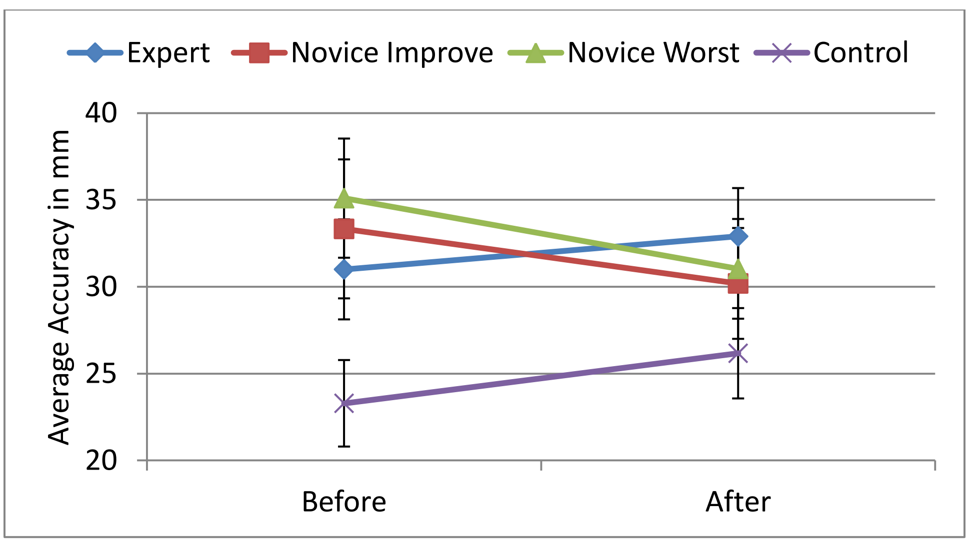


Figure 14. The average accuracy before and after observation by model condition. The control condition refers to the basketball model condition.

The results from the mixed model ANOVA for the average precision can be found in Table 16. For precision, the mixed model ANOVA showed a significant main effect of time (F (1, 82) = 13.972, p = .000, n_p^2 = .101) such that precision was better after the observation phase than before. This result is not surprising as it was expected that physical practice would be sufficient to increase dart throwing performance. Additionally, there was a significant interaction between time and model condition (F (3, 82) = 3.747, p = .014, n_p^2 = .073). Figure 15 shows the average precision by each model condition both before and after the observation phase. Post hoc tests did not reveal significant differences between the precision performances of participants in the different model conditions; however, Figure 15 shows that participants in the expert dart throwing model condition demonstrated the greatest improvement in precision from before to after the observation phase. On the other hand, the participants in the other model conditions showed little to no improvement in precision. This is likely what is driving the significant interaction described above. There were no other significant main effects (p > .05).

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Interaction of Time * Group**
F-test on Precision	F(1, 82) = 13.972, ***p* = .000**, n_p^2 = .101	F(3, 82) = .028, *p* = .994, n_p^2 = .005	F(3, 82) = 3.747, ***p* = .014**, n_p^2 = .073

Table 16. Results from the 4 (model condition) x 2 (before and after performance) mixed model ANOVA for precision performance. The between subjects variable is the model condition and the within subjects variable is the precision performance before and after observation.

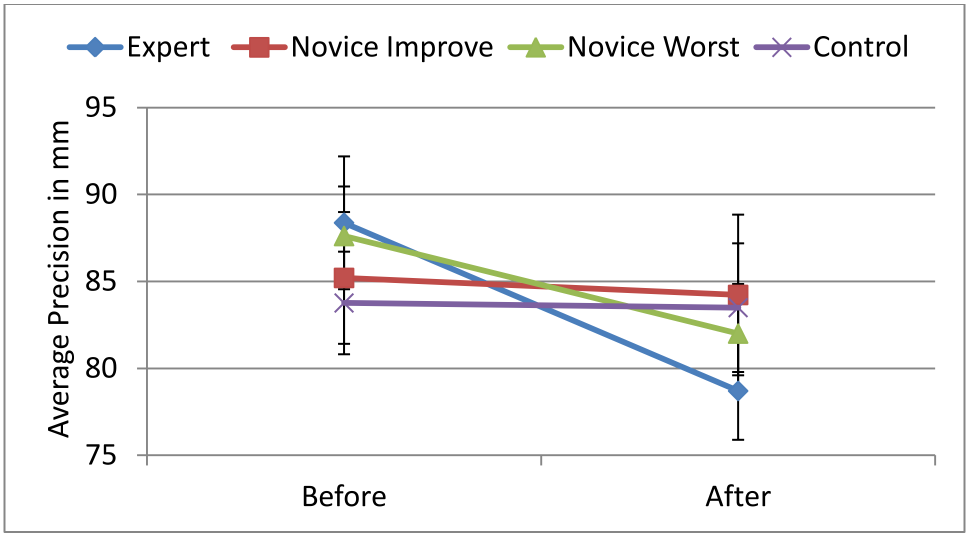


Figure 15. The average precision before and after observation by model condition. The control condition refers to the basketball model condition.

The results for the mixed model ANOVA on the average number of misses can be found in Table 17. A mixed model ANOVA on the average number of misses from before and after the observation phase by model group presented a significant main effect of time (F (1, 82) = 5.785, *p* = .018, n_p^2 = .137) and a significant interaction between time and model condition (F (3, 82) = 3.919, *p* = .011, n_p^2 = .040). There was no main effect of the model condition group (*p* > .05).

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Interaction of Time * Group
F-test on Misses	F(1, 82) = 5.785, ***p* = .018**, n_p^2 = .137	F(3, 82) = .401, *p* = .752, n_p^2 = .015	F(3, 82) = 3.919, ***p* = .011**, n_p^2 = .040

Table 17. Results from the 4 (model condition) x 2 (before and after performance) mixed model ANOVA for average number of misses. The between subjects variable is the model condition and the within subjects variable is the average number of misses before and after observation.

The main effect of time signifies that participants overall missed the target less after the observation phase as compared to before observation, which is expected. In terms of the significant interaction, while post hoc analyses did not indicate significant differences between the experimental groups, the graph for the interaction between time and model condition (Figure 16) shows that participants in all of the model conditions had approximately the same or fewer misses after observation as compared to before. However, participants in the expert dart throwing model condition demonstrated the greatest improvement, throwing fewer misses after observation.

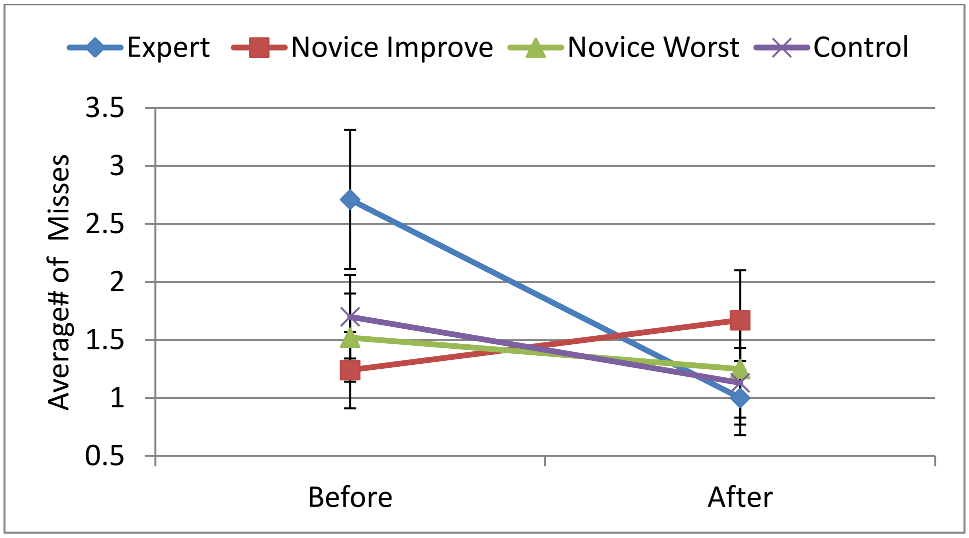


Figure 16. The average number of misses before and after observation by model condition. The control condition refers to the basketball model condition.

Lastly, the results for the mixed model ANOVA for the average number of bounces before and after the observation phase by model group (see Table 18) demonstrated no main effects for time or for experimental group ($p > .05$). Additionally, there was no interaction for the average number of bounces before and after observation as a result of experimental video condition ($p > .05$).

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Interaction of Time * Group**
F-test on Bounces	$F(1, 82) = 1.112$, $p = .295$, $n_p^2 = .056$	$F(3, 82) = .415$, $p = .743$, $n_p^2 = .045$	$F(3, 82) = 1.312$, $p = .276$, $n_p^2 = .077$

Table 18. Results from the 4 (model condition) x 2 (before and after performance) mixed model ANOVA for average number of bounces. The between subjects variable is the model condition and the within subjects variable is the average number of bounces before and after observation.

Individual differences in dart throwing performance. As with Experiment 1, analyses were conducted to test if the participants' general athletic abilities influenced dart throwing performance as a function of model condition. The overall participant sample was divided into quartiles based on their dart throwing accuracy and precision in the familiarization phase (before observation). The top performing participants were compared to the bottom performing participants in a 4 (model condition) x 2 (top and bottom quartiles) x 2 (before and after performance) mixed model ANOVA for accuracy, precision, misses, and bounces. A total of 19 participants comprise the top performing participants (n = 4 expert model condition, n = 5 novice improve model condition, n = 2 novice worst model condition, n = 9 basketball model condition). A total of 20 participants were included in the analyses as the bottom quartile performers (n = 6, expert model condition, n = 7 novice improve model condition, n = 7 novice worst model condition, n = 1 basketball model condition).

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Main Effect of Quartile**	**Interaction of Time * Group**	**Interaction of Time * Quartile**	**3 way interaction Time* Group* Quartile**
F-test on Accuracy	$F(1, 31) = 1.345$, $p = .255$, $n_p^2 = .056$	$F(3, 31) = 1.370$, $p = .270$, $n_p^2 = .117$	$F(1, 31) = 72.824$, $\mathbf{p = .000}$, $n_p^2 = .701$	$F(3, 31) = 1.480$, $p = .239$, $n_p^2 = .125$	$F(1, 31) = 2.591$, $p = .118$, $n_p^2 = .077$	$F(3, 31) = .917$, $p = .444$, $n_p^2 = .082$

Table 19. Results from 4 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for accuracy. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the accuracy performance before and after observation.

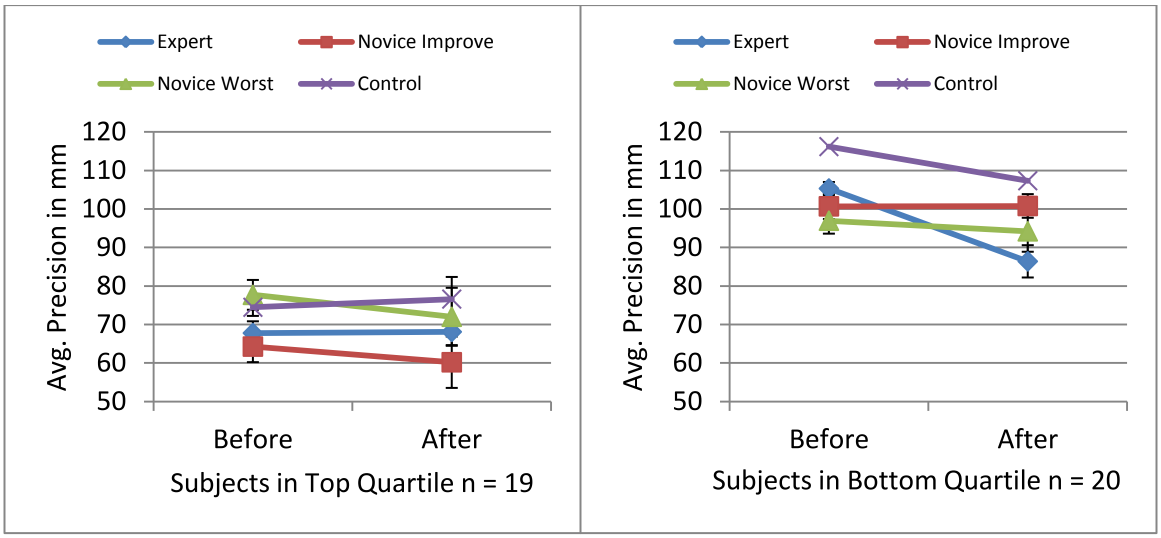
The results of the mixed model ANOVA for accuracy are shown in Table 19 above. Similar to Experiment 1, there was a significant main effect of quartile ($F(3, 31) = 72.824$, $p = .000$, $n_p^2 = .701$) such that participants in the top quartile performed better than participants in the bottom quartile. This main effect was expected to be significant because participants in the top and bottom quartiles were selectively used in these analyses based on dart throwing performance before the observation phase. No other main effects or interactions were significant (p > .05).

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Main Effect of Quartile**	**Interaction of Time * Group**	**Interaction of Time * Quartile**	**3 way interaction Time* Group* Quartile**
F-test on Precision	F(1, 31) = 4.937, ***p* = .034**, n_p^2 = .137	F(3, 31) = 1.828, p = .163, n_p^2 = .150	F(1, 31) = 71.819, ***p* = .000**, n_p^2 = .698	F(3, 31) = .807, p = .499, n_p^2 = .072	F(1, 31) = 1.852, p = .183, n_p^2 = .056	F(3, 31) = 2.384, ***p* = .088**, n_p^2 = .187

Table 20. Results from 4 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for precision. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the precision performance before and after observation.

The results of the mixed model ANOVA for precision are shown in Table 20 above. This analysis revealed a significant main effect of time (F (1, 31) = 4.937, p = .034, n_p^2 = .137) such that overall precision was better after the observation phase than before. In addition, a significant main effect for precision was revealed based on quartile (F (3, 31) = 71.819, p = .000, n_p^2 = .698) in which participants in the top performing quartile were more precise at dart throwing than participants in the bottom performing quartile. Interestingly, there was a marginally significant three-way interaction between time, model group, and quartile. Figures 17 and 18 depict the average precision before and after observation by model condition group for the participants in the top quartile (Figure 17) and participants in the bottom quartile (Figure 18).

Participants in the top quartile demonstrate similar performance in terms of precision both before and after the observation of the video stimuli. Participants in the bottom quartile and who viewed the novice improve or novice worst dart throwing model also performed equally before and after the observation phase. However, participants in the bottom quartile and also in the expert dart throwing model condition or basketball model condition showed improvement in precision after the observation phase. A series of one-way ANOVAs were conducted to determine if there are significant differences between 1) participants in the top quartile before observation, 2) participants in the top quartile after observation, 3) participants in the bottom quartile before observation, and 4) participants in the bottom quartile after observation.



Figures 17 and 18. The average precision before and after the observation phase by model condition group for the top performing participants (Figure 17 on left) and the worst performing participants (Figure 18 on right). The control condition refers to the basketball model condition.

Comparing top performing participants by model condition before the observation phase revealed a marginally significant difference in precision (F (3, 15) = 2.999, *p* = .064, n_p^2 = .375). Top performing participants in the novice improve model condition were marginally more precise at throwing darts than participants in the basketball model control condition in the familiarization phase (F (3, 15) = 2.999, *p* = .103). There were no significant differences amongst the model conditions for top performing individuals after the observation phase (F (3, 15) = 1.237, *p* = .331, n_p^2 = .198). A one-way ANOVA for bottom performing participants by experimental group before the observation phase was not significant (F (3, 16) = 2.637, *p* = .109, n_p^2 = .307). Additionally, examining the bottom quartile by experimental group after the observation phase also not reveal differences amongst the groups (F (3, 16) = 2.099, p = .141, n_p^2 = .282). Overall, this significant three-way interaction between time, experimental group and quartile is not readily interpretable.

A mixed model ANOVA for misses (darts that landed outside the target on the backboard) by model condition and quartile showed a marginally significant main effect of time (F (1, 31) = 3.650, *p* = .065, n_p^2 = .105), and a significant main effect of quartile (F (1, 31) = 27.713, *p* = .000, n_p^2 = .472) (see Table 21 for all results). Overall, participants threw fewer misses after the observation phase than before. Furthermore, the participants in the top quartile outperformed the participants in the bottom quartile in terms of misses. No other main effects or interactions reached significance (*p* > .05).

	Main Effect of Time (before/after)	**Main Effect of Group (model condition)**	**Main Effect of Quartile**	**Interaction of Time * Group**	**Interaction of Time * Quartile**	**3 way interaction Time* Group* Quartile**
F-test on Misses	F(1, 31) = 3.650, ***p* = .065**, n_p^2 = .105	F(3, 31) = .688 *p* = .566, n_p^2 = .062	F(1, 31) = 27.713, ***p* = .000**, n_p^2 = .472	F(3, 31) = 2.081, *p* = .123, n_p^2 = .168	F(1, 31) = 2.535, *p* = .121, n_p^2 = .076	F(3, 31) = 1.132, *p* = .351, n_p^2 = .099

Table 21. Results from 4 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for the average number of misses. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the average number of misses before and after observation.

As can be seen in Table 22, the mixed model ANOVA for bounces by model condition and quartile revealed several main effects and interactions. As in previous analyses, there was a significant main effect of time (F (1, 31) = 5.230, *p* = .029, n_p^2 = .144) such that participants threw fewer bounces (darts that bounced off the board) after the observation phase as compared to before. Additionally, there was a significant main effect of quartile (F (1, 31) = 4.642, *p* = .039, n_p^2 = .130) indicating that participants in the top quartile threw fewer bounces than participants in the bottom quartile.

	Main Effect of Time (before/after)	Main Effect of Group (model condition)	Main Effect of Quartile	Interaction of Time * Group	Interaction of Time * Quartile	3 way interaction Time* Group* Quartile
F-test on Bounces	F(1, 31) = 5.230, ***p* = .029**, n_p^2 = .144	F(3, 31) = .118 *p* = .949, n_p^2 = .011	F(1, 31) = 4.642, ***p* = .039**, n_p^2 = .130	F(3, 31) = 2.613, ***p* = .069**, n_p^2 = .202	F(1, 31) = 5.098, ***p* = .031**, n_p^2 = .141	F(3, 31) = 1.966, *p* = .140, n_p^2 = .160

Table 22. Results from 4 (model condition) x 2 (quartile) x 2 (before and after performance) mixed model ANOVA for the average number of bounces. The between subjects variable is the model condition and quartile (top or bottom quartile) and the within subjects variable is the average number of bounces before and after observation.

A marginally significant interaction between the model condition and the average number of bounces before and after the observation phase was revealed by a mixed model ANOVA (F (3, 31) = 2.613, *p* = .069, n_p^2 = .202). However, post hoc tests did not reveal significant differences amongst the experimental groups for the average number of bounces when combining the data from subjects in the top and bottom quartiles. Figure 19 demonstrates, however, that the novice improve model condition threw more bounces after the observation phase than before. It should be noted, as with Experiment 1, bounces occurred very infrequently, only occurring 2% of the time for the total participant sample.

Finally, the mixed model ANOVA for bounces indicated that there was a significant interaction between quartiles and the average number of bounces before and after the observation phase (F (1, 31) = 5.098, *p* = .031, n_p^2 = .141). This interaction is driven by a significant difference between the participants in the top and bottom quartiles before the observation phase for the average number of bounces (t (27.337) = -3.117, p = .004). Participants in the top quartile threw fewer bounces before the observation phase than participants in the bottom quartile (see Figure 20). No other main effects or interactions were significant (*p* > .05).

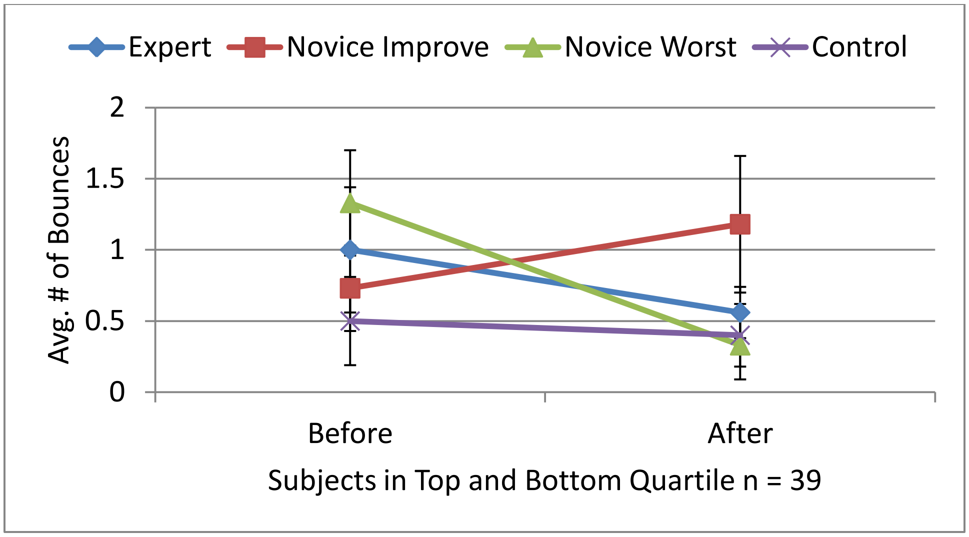


Figure 19. The average number of bounces before and after observation by model condition for participants in the top and bottom quartiles combined. The control condition refers to the basketball model condition.

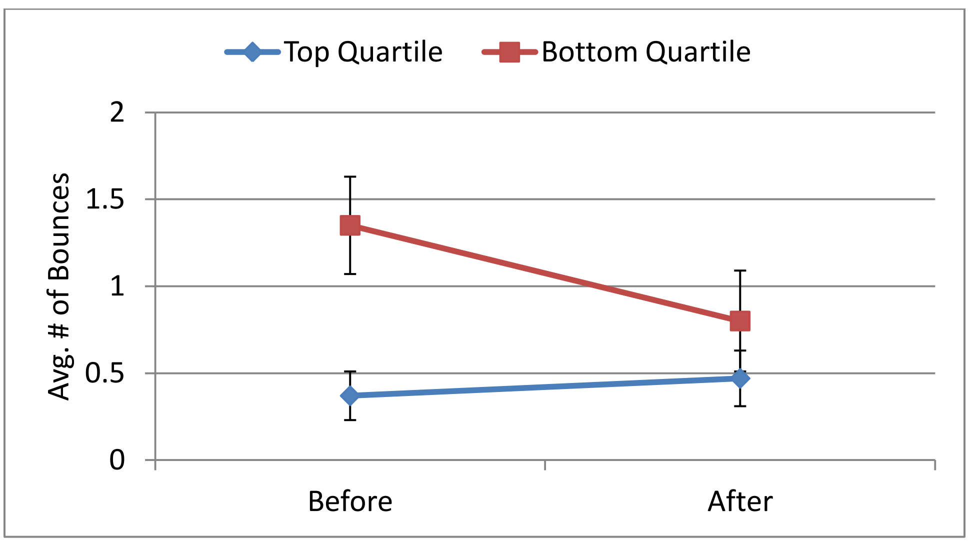


Figure 20. The average number of bounces before and after observation by participants in the top and bottom quartiles.

Improvement of dart throwing over time. In Experiment 1, difference scores were calculated to examine changes in motor performance over time as opposed to aggregate motor performance scores from before and after the observation phase. Similarly, for Experiment 2, changes in performance over time were measured by first combining accuracy and precision performance into phases (see Table 23). In Experiment 2, participants only threw 15 sets of darts before observation and 15 sets of darts after observation. Unlike Experiment 1, a phase consists of only three sets of darts in Experiment 2. Phases 1 – 5 represent participants' performance before the observation of the model while Phases 6 – 10 represent participants' performance after the observation phase. Figures 21 and 22 shows the average accuracy of each experimental group (Figure 21) and the average precision of each experimental group (Figure 22) over the course of the entire experiment.

Phase	**Definition**
Phase1	Dart throwing performance in Sets 1-3 (before video)
Phase2	Dart throwing performance in Sets 4-6 (before video)
Phase3	Dart throwing performance in Sets 7-9 (before video)
Phast4	Dart throwing performance in Sets 10-12 (before video)
Phase5	Dart throwing performance in Sets 13-15 (before video)
Phase6	Dart throwing performance in Sets 1-3 (after video)
Phase7	Dart throwing performance in Sets 4-6 (after video)
Phase8	Dart throwing performance in Sets 7-9 (after video)
Phase9	Dart throwing performance in Sets 10-12 (after video)
Phase10	Dart throwing performance in Sets 13-15 (after video)

Table 23. Description of phase data by dart throwing sets for Experiment 2. Each phase consists of three set of darts (or nine individual dart throws). Phase data were plotted for accuracy and precision performance by model condition.

Before the observation phase, difference scores were calculated for accuracy and precision by subtracting participants' average performance in Phase 1 from Phase 5 (Phase 5 – Phase 1). Negative difference scores indicate improved performance from Phase 1 to Phase 5 while positive difference scores indicate a decline in performance. The Phase 1 to Phase 5 difference scores are displayed in Table 24.

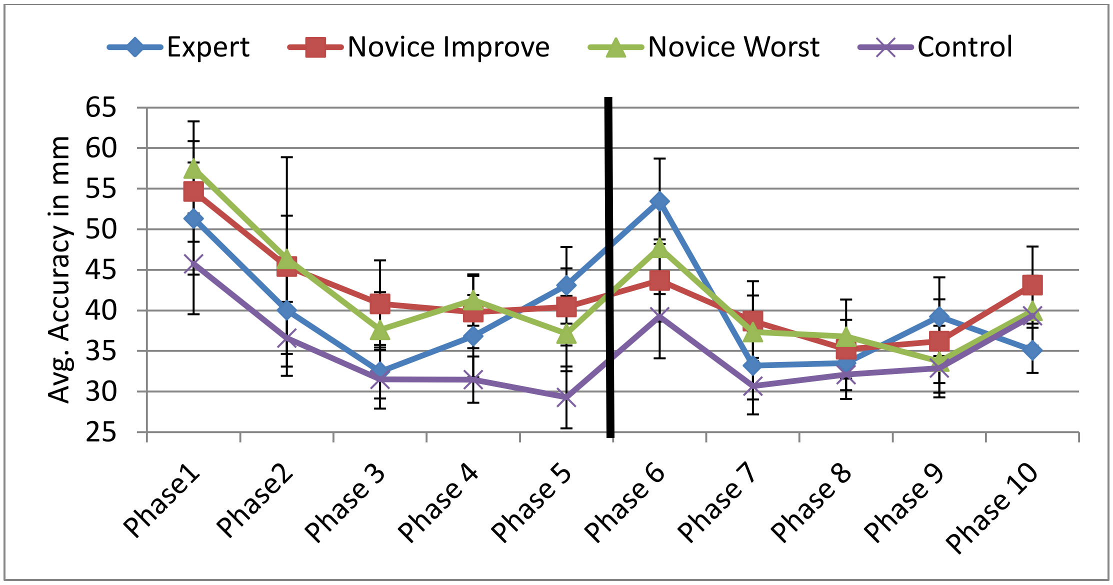


Figure 21. The average accuracy by model condition for Phases 1 – 5 before observation and Phases 6 – 10 after observation. The vertical black line between Phases 5 and 6 represents the observational period. The control condition refers to the basketball model condition.

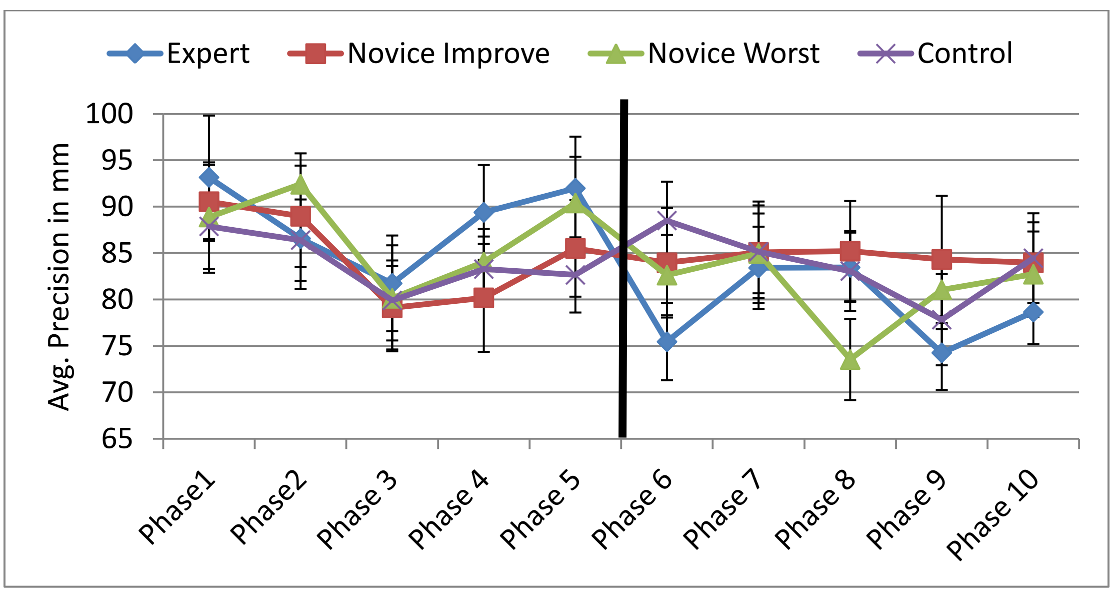


Figure 22. The average precision by model condition for Phases 1 – 5 before observation and Phases 6 – 10 after observation. The vertical black line between Phases 5 and 6 represents the observational period. The control condition refers to the basketball model condition.

Model Condition	**Accuracy Difference Score Before**	**Precision Difference Score Before**
	(Phase 5 – Phase 1)	*(Phase 5 – Phase 1)*
Expert Video	-8.225 (SE = 6.55)	-1.181 (SE = 6.70)
Novice Improve Video	-14.231 (SE = 6.70)	-5.037 (SE = 4.15)
Novice Worst Video	-20.338 (SE = 7.02)	1.514 (SE = 6.23)
Basketball Control Video	-16.464 (SE = 7.34)	-5.227 (SE = 5.27)

Table 24. Accuracy and precision difference scores from before observation calculated by subtracting the average accuracy and precision scores for each experimental group in Phase 1 from the average accuracy and precision scores for each group in Phase 5.

Overall, each experimental group demonstrated improvement in accuracy from Phase 1 to Phase 5. A one-way ANOVA, however, showed no significant differences amongst the groups in terms of their rate of improvement before the observation phase (F (3, 82) = .523, p = .668, n_p^2 = .019). For precision, little improvement was noted for the experimental groups. A one-way ANOVA confirmed that the experimental groups did not differ from one another in terms of change in precision before the observation phase (F (3, 82) = .330. p = .804, n_p^2 = .012). For both accuracy and precision before the observation phase, the experimental groups performed similarly.

Next, difference scores were calculated for performance after the observation phase by subtracting the average accuracy and precision scores in Phase 6 from the average accuracy and precision scores in Phase 10 (Phase 10 – Phase 6). If the manipulation of the video stimuli influences subsequent dart throwing performance, we should see difference in the rate of change for accuracy and precision amongst the experimental groups. The accuracy and precision difference scores for each experimental group after observation are in Table 25.

For both accuracy and precision after the observation phase, all of the experimental groups demonstrated little change after observation with the exception of the participants in the expert model condition. Participants in the expert model condition showed a much greater improvement for accuracy than the other experimental groups after observation of the video stimulus. A one-way ANOVA for accuracy difference scores did not reach significance, but was trending towards significance (F (3, 82) = 2.023, p = .117, n_p^2 = .069). A one-way ANOVA for precision difference scores after observation confirmed no statistical differences amongst the groups (F (3, 82) = .421, p = .739, n_p^2 = .015).

Model Condition	**Accuracy Difference Score After**	**Precision Difference Score After**
	(Phase 10 – Phase 6)	*(Phase 10 – Phase 6)*
Expert Video	-18.364 (SE = 5.65)	3.192 (SE = 4.72)
Novice Improve Video	-.5737 (SE = 3.68)	.001 (SE = 4.46)
Novice Worst Video	-7.757 (SE = 7.92)	.1020 (SE = 5.27)
Basketball Control Video	.1204 (SE = 6.05)	-4.061 (SE = 4.15)

Table 25. Accuracy and precision difference scores from after observation calculated by subtracting the average accuracy and precision scores for each experimental group in Phase 6 from the average accuracy and precision scores for each group in Phase 10.

One potential issue we addressed in analyzing the phase data for accuracy and precision in Experiment 1 is the possibility of participants becoming fatigued in Phases 5 and 10. In Experiment 1, participants threw 25 sets of darts (75 individual dart throws) before observation and again after observation. However, in Experiment 2 the number of dart throws was limited to 15 sets of darts (45 individual dart throws) before observation and after observation to prevent fatigue. While fatigue does not appear to be an issue for Experiment 2 by according to Figures 21 and 22, however, for cohesiveness in statistical analyses between Experiment 1 and 2 accuracy and precision difference scores were calculated to omit data Phases 5 and 10. Therefore, the accuracy and precision difference scores for before the observation phase were calculated by subtracting the average scores in Phase 1 from Phase 4 (Phase 4 – Phase1). After the observation phase, accuracy and precision difference scores were the result of subtracting the average scores in Phase 6 from Phase 9 (Phase 9 – Phase 6). The subsequent accuracy and precision difference scores for each experimental group are presented in Table 26.

Model Condition	**Accuracy Difference Score Before**	**Precision Difference Score Before**
	(Phase 4 – Phase 1)	*(Phase 4 – Phase 1)*
Expert Video	-14.486 (SE = 7.94)	-3.764 (SE = 6.38)
Novice Improve Video	-14.864 (SE = 6.79)	-10.368 (SE = 5.58)
Novice Worst Video	-16.211(SE = 6.14)	-4.850 (SE = 6.20)
Basketball Control Video	-14.270 (SE = 6.38)	-4.598 (SE = 5.43)

Model Condition	**Accuracy Difference Score After**	**Precision Difference Score After**
	(Phase 9 – Phase 6)	*(Phase 9 – Phase 6)*
Expert Video	-14.218 (SE = 7.00)	-1.194 (SE = 4.25)
Novice Improve Video	-7.479(SE = 6.56)	.3647 (SE = 7.28)
Novice Worst Video	-14.014 (SE = 7.17)	-1.574 (SE = 3.41)
Basketball Control Video	-6.312 (SE = 6.01)	-10.675 (SE = 5.29)

Table 26. Accuracy and precision difference scores from before observation (top) calculated by subtracting the average accuracy and precision scores for each experimental group in Phase 4 from the average accuracy and precision scores for each group in Phase 1. Accuracy and precision difference scores for after observation (bottom) were calculated by subtracting the average accuracy and precisions scores for each experimental group in Phase 9 from the average scores in Phase 6.

Participants in all of the experimental groups demonstrated improvement for both accuracy and precision before the observation phase based on the Phase 4 – Phase 1 difference scores. However, a one-way ANOVA for accuracy difference scores before the observation phase revealed no significant differences between the groups (F (3, 82) = .016, p =.997, n_p^2 = .001). Similarly, there were no statistical differences between the groups for change in precision before observation (F (3, 82) = .258, p =.856, n_p^2 = .009). After the observation phase, all of the experimental groups' accuracy improved but the accuracy difference scores were not statistically different from one another (F (3, 82) = .398, p = .755, n_p^2 = .014). In terms of change in precision after the observation phase, the participants in the control condition showed the greatest improvement. However, the differences amongst the model conditions were not significant (F (3, 82) = .943, p = .424, n_p^2 = .033). Thus, when only taking into account the data from Phase 1 through 4 and

Phases 6 through 9, all of the experimental groups demonstrated similar rates of improvement for accuracy and precision.

Finally, a set of accuracy and precision scores were calculated for before and after observation for each experimental group to include data from more than one phase. These difference scores were calculated as the following (see Table 27 for results):

- Before observation: (Average scores of Phases 4 & 5) – (Average scores of Phases 1 &2)
- After observation: (Average scores of Phases 9 & 10) – (Average scores of Phases 6 & 7)

Model Condition	**Accuracy Difference Score Before**	**Precision Difference Score Before**
	(Phase 4&5 – Phase 1&2)	*(Phase 4&5 – Phase 1&2)*
Expert Video	-5.706 (SE = 5.87)	.8215 (SE = 4.16)
Novice Improve Video	-9.918 (SE = 7.12)	-6.916 (SE = 3.60)
Novice Worst Video	-12.714(SE = 4.85)	-3.432 (SE = 3.75)
Basketball Control Video	-10.790 (SE = 4.65)	-4.174 (SE = 3.33)

Model Condition	**Accuracy Difference Score After**	**Precision Difference Score After**
	(Phase 9&10 – Phase 6&7)	*(Phase 9&10 – Phase 6&7)*
Expert Video	-6.166 (SE = 4.42)	-2.978 (SE = 3.26)
Novice Improve Video	-1.525(SE = 4.09)	-.3781 (SE = 4.03)
Novice Worst Video	-5.697 (SE = 4.39)	-1.904 (SE = 3.32)
Basketball Control Video	1.178 (SE = 4.21)	-5.681 (SE = 3.26)

Table 27. Accuracy and precision difference scores from before observation (top) calculated by subtracting the average accuracy and precision scores for each experimental group in Phases 5 and 4 from the average accuracy and precision scores for each group in Phases 1 and 2. Accuracy and precision difference scores for after observation (bottom) were calculated by subtracting the average accuracy and precisions scores for each experimental group in Phases 9 and 10 from the average scores in Phases 6 and 7.

Before the observation phase, there were no differences amongst the groups for change in accuracy ($F (3, 82) = .287$, $p = .849$, $n_p^2 = .010$) or for change in precision ($F (3, 82) = .730$, $p = .537$, $n_p^2 = .026$). After the observation phase, the groups all performed similarly in terms of change in accuracy ($F(3, 82) = .686$, $p = .563$, $n_p^2 = .024$) and change in precision ($F(3, 82) = .426$, $p = .735$, $n_p^2 = .015$).

2.2.4 Discussion.

Previous research focusing on observational learning has shown that observing a model is beneficial to learning a novel motor skill. This has been demonstrated both with a novice model (Blandin et al., 1999; Buchanan et al., 2008; Mattar & Gribble, 2005; Brown et al., 2009) and an expert model (Heyes & Foster, 2002; Bird & Heyes, 2005; Al-Abood et al., 2001). In relation to action understanding theories, observational learning from a novice model is most likely possible through a direct matching process (Rizzolatti et al., 2001). Novice participants and novice models share similar motor repertoires which allow a novice participant to direct match observed actions of the novice model. However, observational learning from an expert model, in which the motor repertoires of the novice participants and expert model are not similar, may occur through action reconstruction (Csibra, 2008). In learning a novel motor task, a novice participant and an expert model share a similar action goal (e.g. accurate dart throwing) and from that goal a novice participants can utilize the visually consistent and accurate performance of the expert model to inform their own motor performance.

The intended goal of Experiment 2 was to elucidate the results from Experiment 1 and to establish what type of processes serves observational learning. In Experiment 1, participants' improvement at the dart throwing task could be attributed to either physical practice or all of the participants observing dart throwing of some kind. Therefore, a model condition was added such that the motor task observed was irrelevant to dart throwing in Experiment 2. The basketball model condition was included as previous research demonstrated a perceptual-motoric link with a basketball task (Sebanz & Shiffrar, 2009) as well as basketball's visual similarity to dart throwing (e.g. pendular arm movement). It was not expected that participants in the basketball condition should demonstrate the same level of improvement as participants in the dart throwing conditions because the task observed is irrelevant to dart throwing.

The results from Experiment 2 revealed no significant benefit in observing the novice model improve in dart throwing, unlike previous research (Blandin et al., 1999; Buchanan et al., 2008; Mattar & Gribble, 2005; Brown et al., 2009). The change in accurate and precise physical performance of dart throwing from before to after the observation phase was not significantly different across the model conditions. Furthermore, there were no differences in the rate of change for accuracy and precision over the course of the experiment by experimental group. When comparing the top performing participants and bottom performing participants in Experiment 2, some similarities to Experiment 1 emerged. Participants in the bottom quartile who viewed either the expert dart thrower video or the basketball model demonstrated improvement for dart throwing precision while those who viewed the novice improve or novice worst model demonstrated no change in precision. A loose interpretation of this could support the action reconstruction hypothesis, however, given that participants in the basketball model condition performed similarly to the other model conditions this suggests improvements in precision are due to physical practice. In conclusion, Experiment 2 did not reveal that the type of model participants observed did not inform subsequent dart throwing performance.

The results from Experiments 1 and 2 lend little support to either the direct matching theory (Rizzolatti et al., 2001) or the action reconstruction theory (Csibra, 2008). Furthermore, the outcomes of these experiments offer little support to the benefits of a novice model versus an expert model. Indeed, the current results are similar to findings by Rohnbadfard and Proteau (2011). In that study, while observing an expert model did benefit observers more than observing a novice model in some respects, the authors' conclusion was that observing a combination of an expert model and novice model was most advantageous to learning. Experiments 1 and 2 did not elucidate whether the observation of one model type was superior to the other. Future work could examine the benefits of observing both the expert and novice models during the observation phase. However, Experiment 2 aimed to determine if observing any type of dart throwing improves observational learning or if the participants' improvements in accuracy and precision witnessed in Experiment 1 were simply the result of physical practice. Participants in Experiment 2 who viewed the basketball control video did not differ significantly in their dart throwing abilities from participants who viewed dart throwing models. In sum, this result suggests that physical practice is sufficient to account for the changes in dart throwing accuracy and precision found in Experiments 1 and 2. Implications of these conclusions will be discussed further in the general discussion of Experiments 1 and 2.

Limitations. As with Experiment 1, the effect size of the model type manipulation was small. Overall, the sample size for Experiment 2 was still small. Mattar & Gribble (2005), from which the design of Experiments 1 and 2 were based, had a sample size of 42 participants per condition. However, based on the relatively small effect sizes found in Experiments 1 and 2, running the number of participants needed to reach significance seems arbitrary. Furthermore, the addition of the basketball model control condition, the results can be attributed to physical practice alone. Essentially, either the experimental manipulations in Experiments 1 and 2 were not sufficiently powerful or observational learning with complex motor tasks, such as dart throwing, involves additional or different processes than observational motor learning simple motor tasks (e.g., button presses). There are several ways in which future work might increase effect sizes. First, Experiments 1 and 2 only implemented one short observational phase between physical performance in the familiarization and test phases. This design has been successfully applied in previous research (see Mattar and Gribble, 2005), however, this may not be effective for an ecologically valid, complex motor skill such as dart throwing. Observation learning studies have used varied schedules of physical practice interspersed with observation of models. For a task as difficult as dart throwing, it may be that participant need to physically and observationally practice dart throwing over the course of several days. In other words, instead of "cramming" practice right before the test phase, participants may need to practice over the course of at least a week. Although there were improvements in overall dart throwing motor performance in these experiments, it is not clear if these improvements would be retained. During the short duration of the experiments, the physical and visual experience participants gained with dart throwing may not result in *learning* to throw darts better. Long term retention of motor learning tends to be the result of spaced practice while massed practice leads to immediate changes in motor performance (Rosenbaum, Carlson, & Gilmore, 2001). Furthermore, research on the formation of motor memories has shown that the consolidations of motor learning into long term memory takes at least five and a half hours, and becomes more robust with increased time (Shadmehr & Brasher-Krug, 1997; Shademehr & Holcomb, 1997). Such evidence suggests that it might be useful to run a modified version of the current study such that each participant has a week of observational and motor learning experience.

Despite the fact that observation of a model did not benefit the physical performance of dart throwing, it remains possible that physical practice and motor observation of dart throws might produce differences in visual discriminative abilities during observed dart throwing. To explore this possibility, Experiments 3 and 4 examined differences in a perceptual task related to dart throwing as opposed to the physical task of dart throwing.

2.3 General Discussion of Experiments 1 and 2

Studies focusing on purely motor skill acquisition (without the observation of a model), have made a distinction between early or “fast” motor learning versus late or “slow” motor learning (Anguera et al., 2010). When first learning to perform a novel motor skill, the early stages of learning are characterized as “fast” because participants can demonstrate a notable improvement in performance over a limited number of trials and within a short period of time (Fitts & Posner, 1967). Early, or “fast”, motor learning is also thought to be more cognitively demanding as the prefrontal cortex is active during early motor learning, but not late motor learning (Anguera, Russell, Noll, & Seidler, 2007). Late, or “slow” learning is characterized by smaller improvements in performance over the course of longer periods of time (Fitts & Posner, 1967). Research on motor skill acquisition has examined the cognitive influences of early motor learning, which distinctly differentiates early learning from late learning. Of importance to Experiments 1 and 2 did not consider early or late motor learning or other possible cognitive factors related to the task.

Anguera and colleagues (2010) aimed to determine the relationships between spatial working memory and motor learning through a visuomotor adaptation task. Visuospatial working memory is a part of the memory system in which spatial information is actively manipulated, as in mental rotation tasks (Baddeley & Hitch, 1974). In addition to the behavioral measures, Anguera and colleagues (2010) measured spatial working memory capacities using a mental rotation task while participants were in the fMRI scanner to pin down the neural correlates. Participants also completed a visuomotor adaptation task while in the fMRI scanner. In this visuomotor adaptation paradigm, participants performed movements using a joystick to maneuver a cursor to different targets. Visual feedback of the cursor movement was veridical during initial training. In other words, if participants moved the joystick north towards a target, the cursor in fact moved north. When distorted feedback was introduced after several practice blocks with veridical feedback, participants were required to compensate in order to successfully reach the desired target. For example, participants may have moved the joystick north, but the cursor moved northeast. To reach the desired target (north), participants had to move the joystick northwest to compensate for the distorted cursor movement. Anguera and colleagues (2010) designated the early motor learning phase as the first three blocks of trials following the introduction of distorted feedback. The results corroborated with previous descriptions of early and late motor learning. In the early learning trials, participants demonstrated rapid gains in performance as compared to the late learning trials. Furthermore, performance on the mental rotation task, which measures visuospatial working memory, was correlated with the early, but not late, learning blocks suggesting that early learning is indeed more cognitively demanding. Brain activations during these tasks revealed an overlap of activation in the dorsolateral prefrontal cortex (DLPFC) when participants were performing the mental rotation task and in the early learning blocks of the visuomotor adaptation task. The overall conclusion was that early motor learning of a visuomotor adaptation task requires cognitive resources, such as visuospatial working memory. Such cognitive resources appear less necessary later in motor learning. A related study (Bo & Seidler, 2009) found that spatial working memory capacity was also related to speed of performance gains and longer sequence "chunks" in early learning phases for motor sequence learning. This shows that visuospatial working memory is critical in early learning of various different motor tasks.

An ERP study using the same visuomotor adaptation paradigm described above found that brain waves reflect the magnitude of errors during joystick movements and that variations in brain waves were more prominent in early motor learning (Anguera, Seidler, & Gehring, 2009). When the distorted visual feedback was first introduced during the motor task, participants' performance initially declined which was reflected by larger waveforms in early motor learning as compared to late motor learning. Furthermore, larger errors in maneuvering the cursor resulted in larger waveforms than smaller errors only in early learning stages. These results imply that error monitoring may occur more in early motor learning than in later stages of learning.

The above studies provide some indication of differences between early and late motor learning. Currently, the influence of observing of a model during early or late motor learning is unclear. It may be possible that the observation of a model is differentially helpful at different phases of learning. Perhaps if early learning is reliant on cognitive resources, such a visuospatial working memory and error monitoring, then the observation of a model may not be beneficial but rather results in cognitive overload. Another possibility is that in early stages of observational motor learning, motor consolidation takes precedent over the potential benefits of observing a model in order to improve at the motor task. One problem with describing motor learning as "early" or "late" is that there is no unified process to define performance as early or late learning. In each of the studies described above, the definitions of early versus late motor learning stages seemed rather arbitrary. In Experiments 1 and 2, it is unclear where early motor learning ended and late motor learning began, if it began at all. Participants demonstrated appreciable amounts of improvement in the dart throwing accuracy and precision during the familiarization phase. Additionally, they also continued to improve in the test phase, although to a lesser extent. Is this alone enough to characterize the familiarization phase as early motor learning and the subsequent test phase as late motor learning? Based on the design of Experiment 1 and 2, this question remains an open one. Participants never returned to the lab to test motor retention of the dart throwing experience. Furthermore, identifying clear processes to distinguish early versus late motor learning may be dependent on the complexity of the motor task.

In addition to the ambiguity of early and late motor learning stages, another potentially influential factor in Experiments 1 and 2 was the individual differences in general athletic abilities. All of the participants in Experiment 1 and 2 were asked about previous sports experience. Due to the open-ended nature of the question, it was not possible to use this information in the data analyses. Research has shown that individual differences in action experience influence the efficiency with which one learns novel motor skills. Watanabe, Savion-Lemieux, and Penhune (2007) examined the effect of differences in previous musical training on a timing motor task. The participants included musicians who began training before the age of 7, musicians who began training after the age of 7, and non-musicians. The timing task required participants to respond to a 10 element sequence with a key press. The elements were either long or short and in response to each element, participants pressed the key and held the key down for the duration of the element. Early trained musicians (trained before the age of 7) performed more synchronously and accurately than late trained musicians or non-musicians. This suggests that individual differences in previous training in one realm (e.g., music) can be useful during motor learning of a novel task (e.g., timing). Similarly, in Experiments 1 and 2, when examining participants based on superior or poor performance in the initial dart throwing task, top performing participants tended perform well over the course of the experiment as compared to bottom performing participants. It may be the case that the top performing participants in Experiments 1 and 2 had some previous athletic experiences that facilitated performance in the initial dart throwing task.

It does appear as though general motor mechanisms can influence performance in a variety of different athletic tasks. Balance ability is a general motor skill that is often associated with gymnasts. However, many other sports require exceptional balance. A recent review article concluded, unsurprisingly, that gymnasts demonstrate the greatest balance ability (Hrysomallis, 2011). Interestingly, swimmers showed better balance ability than basketball players and inferior balance ability to gymnasts. Furthermore, the more advanced an individual was in certain sports, the better balance ability generally exhibited (Hrysomallis, 2011). This was true of expert rifle shooters, soccer players, and golfers. However, improved balance was not noted for elite skiers, surfers, or judoists. This review article, as it relates to Experiments 1 and 2, could suggest that some common motor mechanism (e.g., balance ability) might influence dart throwing performance such that novice participants, upon entering the experiment, may already differ in their ability to learning how to throw darts. As such, in Experiments 3 and 4, the novice participants performed a psychophysical task, as opposed to a motor task that might have been affected by previous motor experience, to examine perception-action coupling of a complex, ecologically valid motor task.

Chapter 3: Introduction to Experiments 3 and 4

In Experiments 1 and 2, participants were asked to physically perform a dart throwing task before and after the observation of a dart throwing model. While the experimental paradigm employed in these studies may not have led to improved motor performance immediately after observation, a separate possibility remains. Does visual experience and motor experience with dart throwing, or either type of experience in isolation, impact visual sensitivity to observed dart throwing actions?

The literature on perception-action coupling implies that the relationship between the two systems is bi-directional in nature. Many theories of perception-action coupling have posited that perception and action rely on common cognitive representations, often referred to as the common coding theory (Prinz, 1997). Action simulation theories build upon the common coding to include that observing other's actions triggers a simulation process in the observer (Blakemore & Decety, 2001; Jeannerod, 2001; Knoblich, 2008; Wilson & Knoblich, 2005; Wolpert, Doya, & Kawato, 2003). By observing a model perform an action, the visual representation of that action is matched to the observer's motor repertoire such that predicting the action outcome becomes possible. This claim has been supported through studies of visual discrimination and action prediction by athletes, visual and motor experts in their sport. Experiment 3 tests the assumption that motor system engagement during action observation influences action prediction. Furthermore, learning a novel motor skill through kinematic feedback can lead to improvements in visual discrimination and action prediction tasks related to the skill (e.g., Hecht et al., 2001; Casile & Giese, 2006; Brown et al., 2007; Beets et al., 2010). While sensory feedback from the motor system appears to be sufficient to improve visual sensitivity, it seems reasonable to predict that visual sensitivity to other people's movements might be further enhanced by additional feedback and interaction from the visual system. Experiment 4 tests this prediction.

3.1 Expertise in Sports and Enhanced Visual Sensitivity

Athletes, with years of visual and motor experience playing a sport, provide an opportunity to examine the effects of experience on visual discrimination tasks. Evidence from perception-action coupling studies with athlete participants indicates that athletes exhibit elevated visual sensitivity to the motor activities in their sport. As mentioned above, it is theorized that action simulation occurs through matching an observed action to the observer's own motor repertoire and this in turn allows for success in predicting action outcomes (Blakemore & Decety, 2001; Knoblich, 2008). It follows that action prediction accuracy should increase with increases in the observer's motor expertise. Take the case of rugby, for example. In rugby, offensive players attempt to carry the ball down the field while avoiding defenders. Offensive players may be more successful if they are able to deceive defenders with lateral movements that trick the defenders into thinking that they intend to move one direction when they actually intend to move in another direction. Experienced rugby players not only have physical experience performing such deceptive movements, they also have extensive visual experience with these movements.

Jackson and colleagues (2006) conducted a study measuring rugby players' visual sensitivity to such lateral rugby movements. In this study, expert rugby players and novices viewed videos of a player running towards the camera. On each trial, the player either performed a deceptive lateral move or a non-deceptive running movement towards a target at one side of the camera. When asked to determine if the player's movement on each trial would lead to a leftward or rightward locomotor trajectory, expert rugby players were less likely to "fall for" the deceptive lateral movements as compared to rugby novices. These results suggest that extensive visual and motor experience with rugby affords better visual detection of the deceptive intentions of rugby movements (Jackson et al., 2006).

Additional studies provide similar evidence of superior discriminative abilities in experts proficient in handball (Canal-Bruland & Schmidt, 2009; Canal-Bruland et al., 2010), badminton (Wright et al., 2010), dance (Calvo-Merino et al., 2005; 2006; 2010), tennis (Farrow & Abernathy, 2003), cricket (Mann et al., 2010) and basketball (Sebanz & Shiffrar, 2009; Hohmann et al., 2011). However, the contributions of visual experience and motor experience are typically confounded in such studies. Canal-Bruland and Schmidt (2009) attempted to disentangle these factors by recruiting handball players with different types of motor experience executing deceptive shots. While handball field players and goalkeepers have extensive visual experience with deceptive shots, only field players have motor experience performing deceptive shots. If motor experience performing a skill improves perceptual discrimination then the field players should outperform both goalkeepers and handball novices on tasks measuring visual sensitivity to that skill. In the Canal-Bruland and Schmidt (2009) study, expert handball field players, expert goalkeepers and handball novices viewed videos of a handball player either shooting the ball normally or faking a shot. After viewing each video, observers indicated if the video depicted a true shot or fake shot. The videos ended before the ball left the player's hand. The results demonstrated that both expert field players and goalkeepers were more accurate than novices in discriminating fake shots from true shots, in line with previous research. However, no significant difference was found in the perceptual performance of the field players and goalkeepers. This result suggests that differences in motor expertise do not differentially impact visual sensitivity to motor skills. The experimental design of this experiment as well as a follow-up study (Canal-Bruland et al., 2010), however, make it difficult to differentiate the individual contributions of visual expertise and motor expertise on visual sensitivity to motor skills. While goalkeepers may not be as experienced as field players in making shots, it is likely that goalkeepers have also physically practiced making shots during team training sessions.

Hohmann and colleagues (2011) examined the individual contributions of motor experience and visual experience on visual sensitivity to motor skills in expert basketball players. Athletes have extensive experience performing movements but not seeing their own movements from a third person viewpoint. The stimuli in this experiment consisted of point-light displays of expert basketball players performing various basketball dribbles. The players were then asked to identify each point light dribbler as themselves, players on their team, or players from a different team. The basketball players were most accurate at identifying their own movements in the point light movies, suggesting that motor experience is crucial to experts' enhanced discriminative perception. The results of this study are in line with other research on discrimination of self-produced versus other-produced movements in point-light (Loula et al., 2005; Prasad & Shiffrar, 2009) and full light movies (Knoblich & Flach, 2001).

Research examining the neural correlates of experts' visual discriminations of movements in their own sport also supports the influence of motor experience. Brain imaging studies support the claim that the mirror neuron system is more active when experts observe actions for which they have motor expertise. For example, a now classic fMRI study revealed increases in neural activity within premotor and parietal brain areas, as well as in the superior temporal sulcus, when expert ballet dancers and capoeira dancers watched dance moves they have expertise in as compared to dance moves they do not have expertise in and to control subjects who were not dancers (Calvo-Merino et al., 2005). Thus, the observation of familiar actions activated the mirror neuron system as a function of the motor repertoire of the observer. These results cannot be explained by visual familiarity alone because male and female ballet dancers demonstrate more brain activity in the mirror neuron system when they observe their own gender-specific dance moves in comparison to opposite-gender moves (Calvo-Merino et al., 2006).

With the exception of the studies focusing on handball players (Canal-Bruland & Schmidt, 2009; Canal-Bruland et al., 2010), the above studies support the hypothesis that visual sensitivity to human actions is driven by motor experience and with that the ability to simulate actions more accurately. However, Aglioti and colleagues (2008) demonstrated that visual experience can also prove important as well. They asked expert basketball players (motor and visual experts), basketball coaches (visual experts) and basketball novices to view clips of free throw shots and determine whether each shot would go in the net. Behavioral results replicated the previous studies; expert players were more accurate than coaches or novices. Interestingly, motor evoked potentials (MEP) in the hands and forearms increased for both players and coaches, but not novices, during basketball shot observation. There were no differences in MEPs amongst the groups when watching soccer kicks. Therefore, observing a sport with which one has either visual or motor expertise is sufficient to prime motor system even though psychophysical measures, to date, suggest that motor expertise largely drives visual sensitivity to athletic motor skills.

3.2 Visual Learning of Complex Human Movement

Although the perception-action coupling research on athletes supports the idea that motor experience is more influential on visual sensitivity than visual experience, research has shown that visual discrimination of complex human movement is possible with visual training. Grossman and colleagues (2004) examined behavioral changes and neural correlates associated with visual experience on the discrimination of biological motion. The stimuli were point-light displays of human actors portraying a variety of different actions (e.g., kicking, jogging, and throwing). Point-light displays are created by attaching sensors to an actor's major joints and the head and recording the actor's movement. The resultant stimuli depict only the dots associated with the sensors and are readily recognizable as human movement by observers. Point-light displays are often presented in a point-light mask to increase the difficulty of a task. Point-light masks are achieved by duplicating a point-light person and randomizing the starting location of each dot. By putting a coherent point-light person in a point-light mask, detection of the point-light person depends on global motion detection.

Grossman and colleagues (2004) employed a 2AFC detection task using stimuli that were either coherent point-light people in a point-light mask, or scrambled point-light people in a point-light mask. In the 2AFC detection task conducted before and after visual training, participants judged if a stimulus contained a coherent or scrambled point-light person. No feedback on performance was provided during these measurements. Additionally, participants completed fMRI scanning sessions pre- and post-visual training to determine changes in brain activity when performing the 2AFC detection task. Two brain regions of interest were identified due to their importance in biological motion processing: the posterior region of the superior temporal sulcus (STSp) and the ventral region of the fusiform gyrus, also known as the fusiform face area (FFA). Following the pre-visual training measurements of behavioral performance and brain activity from the fMRI scans, participants visually trained on the 2AFC detection task with feedback over the course of several days. The post-visual training behavioral results showed that all of the participants improved at the detection of coherent and scrambled point-light displays from training. Furthermore, participants were also able to successfully discriminate novel coherent and scrambled point-light displays despite no previous training with these animations. The fMRI results demonstrated BOLD activity increases in the STSp and FFA from pre- to post-visual training. A positive correlation was found such that the more behavioral improvement participants exhibited with the 2AFC detection task, the larger change in BOLD activity was for the regions of interest. Taken together, this study demonstrates that participants can learn to better discriminate complex, biological motion displays and brain activity reflects this visual learning process. However, only two brain regions of interest were examined, and not other brain areas related to action observation or motor learning.

Biological motion is thought to be unique because of the smooth trajectories of the limbs, an underlying form or skeleton, and visual familiarity (Jastorff et al., 2006). In order to investigate if visual learning of complex movement patterns is specific to human movement or can be generalized to other types of complex movement, Jastorff and colleagues (2006) tested point-light displays of human movement and artificial “creature” movement. Some examples of the different actions the point-light people displayed included punching, kicking, marching, and running. The stimuli featuring artificial “creature” movement were similar to human movement stimuli in that the limb trajectories were smooth, but they differed in the underlying skeleton. Participants described the novel forms of the artificial “creature” point-light displays as mechanical devices or “weird spiders”. These displays were not presented in a point-light mask, unlike the paradigm used by Grossman and colleagues (2004). Visual learning of these movement stimuli was assessed using a 2AFC discrimination task. In the 2AFC discrimination task, participants were shown two stimuli sequentially. Participants judged if the second stimulus matched the first stimulus or not. In two test blocks (pre- and post-visual training), participants performed the discrimination task without feedback on performance. Visual training consisted of three blocks of trials in which participants were provided feedback on performance. The results showed that participants improved from pre- to post-visual training at a similar rate for discriminating differences point-light people and point-light creatures. The authors suggest that visual learning mechanisms are sensitive to both human and novel non-human movement. Additionally, discriminative learning occurred very quickly for both types of stimuli.

A subsequent study examined the neural correlates of the visual learning mechanisms responsible for human and non-human movement using a repetition suppression paradigm (Jastorff et al., 2009). A repetition suppression paradigm assumes that as identical stimuli are presented visually, adaption to the stimuli occur resulting in a steady decrease in BOLD signal. If a stimulus is presented and detected as different from the adaptation stimuli, the BOLD signal rebounds, indicating that a brain region is sensitive to differences in the stimuli.

Jastorff and colleagues (2009) identified several brain regions of interest related to the visual learning of complex movements. Before visual training, participants' brains were scanned to localized general motion areas (middle temporal area, MT/V5+; kinetic occipital area KO/V3b), biological motion areas (posterior region of the superior temporal sulcus, STSp; extrastriate and the fusiform body area, EBA/FBA), and frontal brain areas (ventral precentral sulcus, vPrCS; posterior inferior frontal sulcus, pIFS). In the fMRI scanner, participants performed the same 2AFC discrimination task described above (no feedback provided) both before and after visual training. During visual training, which lasted three days, participants were given feedback on their performance during visual discrimination task. The results showed that following visual training, participants were able to discriminate differences in similar looking human and artificial "creature" movement patterns. Brain activity in the general motion areas indicated that the human movement stimuli were not detected as different before training (continued decrease in BOLD signal), but were differentiated after training (rebound in BOLD signal). Areas of the brain related to biological motion processing were sensitive to the human movement stimuli before and after training, as would be predicted. Prefrontal areas of the brain were found to be active when the task was more demanding (e.g. more similar looking stimuli). Activity in the general motor brain areas and biological motion areas indicated that artificial "creature" movement was differentiated only after training. The authors suggest that because the general and biological motion areas of brain demonstrate similar activity to human and artificial “creature” movement after training, that a visual learning mechanism generalizes movement patterns related and unrelated to human motor execution.

Of importance, with visual practice participants can learn to discriminate differences in observed complex movement patterns, some of which can be relevant to motor execution. As previously discussed, research on the mirror neuron system, or more generally the action observation network, demonstrates that a wide range of brain areas are involved in observing and executing human movement. These areas include, but are not limited to, the premotor cortex (Fadiga et al., 1995; Cross et al., 2009), the inferior frontal gyrus and the inferior parietal lobule (Iacoboni, 1999; Kilner et al., 2009; Cross et al., 2006; Cross et al., 2009), the posterior region of the superior temporal sulcus (Calvo-Merino et al., 2005; Cross et al., 2009), the dorsolateral prefrontal cortex (Decety et al., 1997; Cross et al., 2009) and the cerebellum (Calvo-Merino et al., 2006; Cross et al., 2009). It appears that certain areas of the action observation network exhibits unique activation patterns in accordance to abstract action goals but not the differences in kinematics to reach the goal (Hamilton & Grafton, 2006). Other areas of the action observation network appear to encode specific kinematic patterns for complex biological movement (see Kilner & Lemon 2013 for a current review of knowledge relating to the mirror neuron system).

These unique brain activation patterns are in line with the cognitively driven direct matching theory (Rizzolatti et al., 2001) and action reconstruction theory (Csibra, 2008). Furthermore, if observation of actions activates motor areas of the action observation network which theoretically represents a simulation process, then preoccupying the motor system during observation should disrupt the simulation process. This should in turn decrease an observer’s ability to predict action outcomes accurately. The nature of this simulation process as it relates to direct matching and action reconstruction are currently unknown. Experiment 3 aims to examine the influence of motor preoccupation during action observation on predicting action outcomes.

3.3 Motor Learning and Changes in Perception

The perception-action coupling literature with athletes suggests that extensive experience with a sport, especially motor experience, enhances visual sensitivity to movements from that sport. However, in all of the perception-action coupling studies, athlete participants gained their expertise long before participating in the studies. Other studies have investigated the question of whether learning novel motor skills as a novice improves visual discrimination of those skills. These studies investigated visual sensitivity in novice participants who had learned to perform specific types of atypical limb movements actively (Hecht et al., 2001; Casile & Giese, 2006; Brown et al., 2007) or passively (Hecht et al., 2001; Beets et al., 2010) and whether this experience in novices impacts visual sensitivity to velocity (Hecht et al., 2001), the 2/3 power law (Beets et al., 2010), point-light walkers (Casile & Giese, 2006), and object acceleration (Brown et al., 2007). As outlined below, the results of these studies are consistent with the hypothesis that action and perception share common codes (Prinz, 1997). More specifically, this common coding theory posits an overlap between cognitive representations involved in action production and action perception (Wilson, 2001; Hommel et al., 2001; for a review of evidence supporting common coding, see van der Wel et al., 2013). This overlap, in turn, is thought to make possible phenomena such as observational motor learning (perception to action) and the impact of motor experience on visual processes. As new motor skills are acquired, the motor repertoire of the observer changes such that action simulation to the newly acquired motor skill is possible (Knoblich, 2008).

Hecht and colleagues (2001) demonstrated both how visual practice of a task can lead to improvements in a motor test and how motor practice of a task can lead to improvements in a visual test. While observational learning studies have established the benefits of observing a model perform a motor task on an observer's subsequent motor performance, Hecht and colleagues (2001) revealed the opposite phenomenon. Participants produced two cyclical arm movements with a lever at various velocity ratios. The first cyclical arm movement was to be produced at a constant speed while the second cyclical arm movement was performed at a velocity ratio either faster or slower than the first arm movement. There was no concurrent visual feedback of participants' arm movements as all of the participants were blindfolded during the motor practice stage. Following motor practice, these participants were asked to judge the velocity ratios of stimuli on a computer screen. The stimuli featured a dot moving in a cyclical pattern two consecutive times. Similar to the motor practice condition, in the dot's first cycle moved at a constant speed. In the second cyclical movement, the dot would move between 200% faster or 50% slower compared to the first cycle. Participants were asked to judge which of the various velocity ratios observed. The participants who received motor practice performed significantly better than control participants who received no practice suggesting that physical experience performing the cyclical arm movements led to improvements in a related perceptual judgment task. Similarly, Reed and Farah (1995) found that detection of changes in limb positions (arms or legs) in static body stimuli was enhanced when participants physically moved the analogous limb during the task.

Interestingly, the results above suggest that simply the kinesthetic feedback of performing the cyclical arm movements, and not action planning and motor preparation that improved subsequent perceptual judgments (Hecht et al., 2001). In a follow up study, Hecht and colleagues (2001) had participants either actively perform the cyclical arm movements during a motor practice phase or passively perform the same movements (in the latter case participants were yoked to the active participants to elicit passive arm movements). In the case of the active motor practice, these participants received kinesthetic sensory feedback from the arm movements and engaged in active motor planning to perform the cyclical arm movements. The participants who passively performed the same movements only received kinesthetic feedback as they were unable to plan for the cyclical velocity ratios between the two cycle movements. The visual test (judging velocity ratios) following the motor practice showed no differences in performance between the active and passive motor participants. They were equally as good at judging the velocity ratios as compared to control subjects. This study suggests that motor learning, by way of kinesthetic feedback, informs the visual system on related tasks.

Beets and colleagues (2010) additionally went on to answer the question of whether learning a motor skill without visual feedback can improve subsequent performance in a visual discrimination task by focusing on the well-known 2/3rds power law (Viviani & Stucchi, 1992). The 2/3rds power law describes the velocity with which a person can move a limb as a function of the curvature of the limb's trajectory. For instance, if moving the arm in a circle, the 2/3rds power law would predict that movement would occur at a constant velocity because the curvature of a circular trajectory is constant. However, when moving an arm along an elliptical trajectory, the 2/3rds power law predicts that the velocity would change as a function of the instantaneous curvature of the arm's elliptical trajectory. In the Beets and colleagues (2010) study, participants underwent a passive motor training regimen while blindfolded in which they placed their arms into a manipulandum that was programmed to move in a circle at two different velocities profiles. Although the arm was passively moved in a circle, the two velocity profiles (variable not constant velocity) presented during motor training were inconsistent with the 2/3rds power law. A control group of participants were received passive motor training on a linear arm movement. Motor learning was assessed throughout the passive motor training by asking participants to actively perform the circular arm movement at the velocity profile in which they were trained. Furthermore, changes in visual discrimination were evaluated by requiring subjects to judge the velocity of two sequentially presented dots as the same or different. These stimuli either moved at a constant or variable velocity (consistent or inconsistent with the $2/3^{rds}$ power law).

The results demonstrated that passive motor training with a velocity profile inconsistent with the $2/3^{rds}$ power law leads to motor learning of this skill as compared to passive training with linear movements. Furthermore, if participants were passively trained on a velocity profile inconsistent with the $2/3^{rds}$ power law, they performed better in the visual discrimination task after the motor training as compared to control participants. These results suggest that kinesthetic feedback of a motor skill alone can improve subsequent perceptual judgments of a related skill.

In these two studies described above (Hecht et al., 2001; Beets et al., 2010) participants learned a motor skill and then judged degraded stimuli (e.g., dots). Casile and Giese (2006) attempted to determine if motor training in the absence of visual input could influence visual judgments of ecologically valid human motion depicted in point-light displays. The visual discrimination task, conducted both before and after the nonvisual motor training, featured three types of point light walkers: one with a naturally occurring gait and two with atypical gaits. In a naturally occurring gait, if the left foot is leading, the right foot is lagging. Further, if in this same gait the right hand is leading, the left hand is lagging. The ratio between the left/right foot and left/right hand in a naturally occurring gait can be defined as 180 degrees. The two point-light walkers displaying atypical gaits demonstrated ratios between the left/right foot and left/right hand that is unnatural when walking. For these stimuli, the ratios between the limbs were defined as 225 degrees and 270 degrees. In the visual discrimination task, two point-light walkers were presented consecutively and the participants reported whether the walkers portrayed the same or different gait cycles. During the nonvisual motor training, with the assistance of verbal and kinesthetic feedback, participants learned the arm movements associated with one of the atypical gait cycles (270 degrees) while walking on the treadmill blindfolded. Arm movements were preferred for the learning task as attempting to learn the atypical foot movements could lead to serious injury. The results showed that the motor training with arm movements associated with an atypical gait in the absence of visual input was sufficient to improve visual sensitivity to that same atypical gait but not other gait cycles. In other words, participants who received motor training on arm movements for a 270 degree gait cycle demonstrated enhanced visual sensitivity point-light walkers portraying the same 270 degree gait cycle but not to point-light walkers depicting other novel gait cycles (Casile & Giese, 2006). Interestingly, the better a participant learned to execute atypical arm movements, the greater their visual sensitivity to that particular gait cycle. However, this study has been criticized as only two participants were able to learn the atypical gait cycles (Beets et al., 2010).

Finally, Brown and colleagues (2007) examined whether learning relative force information from a motor task informs visual predictions of object acceleration. Participants first performed a motor training task in which they moved a robotic arm in one of three different force fields. The different force field conditions were implemented such that the robotic arm would be pushed leftward, rightward, or have no force at all. Participants had to learn to maneuver the robotic arm and compensate for the force field when trying to reach for various targets. After this motor training phase, participants were asked to “catch” an accelerating target that moved in a straight horizontal line (from the left of the screen to the right) by intercepting the target with the robotic arm. The results demonstrated that subjects learned compensate for the applied force fields during motor training as over practice they showed less curvature in their robotic arm movements toward the targets. As predicted, participants who trained in the rightward force field were more successful at catching the accelerating target (in this condition the direction of the moving target was congruent with the force field) than participants who trained in either the null or leftward force field. These results suggest that motor learning in a novel force field influences visual perception.

The studies summarized above provide evidence that not only does the visual perception of actions inform the motor system (as in observational learning), but that action production can also modulate visual perception of action-related variables. The results of the studies employing nonvisual motor training suggest sensory feedback from the motor system appears to be sufficient to improve visual sensitivity (Hecht et al., 2001; Beets et al., 2010; Casile & Giese, 2006). However, it seems reasonable to predict that visual sensitivity might be further enhanced by interactions of the motor and visual systems. Consistent with this, Iacoboni and colleagues (1999) found that neural activation in cortical areas associated with the mirror neuron system (MNS) is greater during concurrent observation and execution of finger tapping than during either the observation or production of finger taps alone. Experiment 4 aims to determine the influence of nonvisual motor training and visual motor training on predicting action outcomes.

Furthermore, the direct matching hypothesis (Rizzolatti et al., 2001) and the action reconstruction hypothesis (Csibra, 2008) presume that understanding an observed action requires the motor system to be available for a simulation process, such that the observed action is either directly matched to the observer’s motor repertoire or that the observer reconstructs performance of the action based on his or her own motor capabilities. This action simulation process is thought to improve action outcome predictions of observed actions (Blakemore & Decety, 2001; Knoblich, 2008; van der Wel et al., 2013). Of the studies examining the impact of motor skill acquisition on visual sensitivity, only Brown and colleagues (2007) used action prediction as an outcome measure.

3.3 Overview of Experiments 3 and 4

Experiments 3 and 4 collectively aim to examine the impact of integrated visual-motor system activity relative to isolated activity in either system alone on the visual perception of motor behavior. Action simulation theories suggest that observing an action triggers a simulation process in the observer such that predicting the action outcome is possible (Blakemore & Decety, 2001; Knoblich, 2008; van der Wel et al., 2013). Action simulation theories imply that the motor system is engaged during the observation of action and research on the action observation network corroborates this argument. Thus, if the motor system was unable to engage in the simulation process during action observation, action prediction should be inhibited. However, the characteristics of the simulation process, as it relates to the direct matching and action reconstruction theories, remain unknown. The direct matching theory would suggest that action simulation is effector dependent. Action reconstruction theory, on the other hand, would suggest that action simulation is reliant on motor areas related action planning. In Experiment 3 participants performed an action prediction task before and after visual training in an observation phase. During the observation phase of the dart throwing model, participants' motor systems were not preoccupied (leaving the motor system free to simulate the observed actions), or preoccupied (potentially disrupting the simulation process). The motor preoccupation conditions attempt to decipher if action simulation is effector dependent or reliant on action planning.

In Experiment 4, participants performed the same action prediction task from Experiment 3 before and after visual or nonvisual motor training. During the motor training, participants physically performed dart throwing with visual feedback of their throwing arm (allowing both visual and kinesthetic feedback during the motor task), without visual feedback of the throwing arm (permitting only kinesthetic feedback), or physically practiced an unrelated task. The differences in motor training are meant to determine if feedback from both the visual system and motor system is superior to feedback from the motor system alone.

These two studies extend the current research in a couple of ways. First, these studies aim to bridge the gap between the types of real-world actions featured in the perception-action coupling literature (e.g., rugby, basketball, etc.) and the actions in studies demonstrating changes in visual sensitivity as a function of motor learning (e.g., novel arm movements). Dart throwing is an action in which there are experts and novices and it has been shown that predicting dart throwing outcomes is best when observing dart throws the observer produced as compared to dart throws produced by a stranger (Knoblich & Flach, 2001). Furthermore, a novel dart throwing task has been used in observational learning studies (Al-Abood et al., 2001).

Next, the studies are the first to my knowledge that examine the influence of systematically gaining visual and/or motor experience, as all of the participants will be novices, with a real-world action on the ability to correctly predict dart throwing action outcomes. The common coding theory and action simulation theory posit that observation of actions inherently involves the motor system and that predicting action outcomes activates the observer's motor repertoire. Previous studies have isolated the motor system from visual feedback (e.g., Brown et al., 2007) and determined that this alone is sufficient for action prediction. However, if the motor system and visual system are allowed to interact, the ability to predict action outcomes should increase as compared to isolating one system from the other. Additionally, no studies to my knowledge have isolated the visual system by preoccupying the motor system to determine the individual contribution of the visual system in predicting action outcomes.

Chapter 4: Investigating Improvements in Action Prediction with Motor Manipulations during Observation

4.1 Experiment 3: Action Prediction of Observed Dart Throwing: Motor Manipulations

4.1.1 Hypothesis and theoretical motivation.

Experiment 3 examined changes in action outcome prediction as a function of the amount of interaction between the visual system and motor system by systematically preoccupying the motor system to various degrees. Neuroscience research has shown that observing an action recruits motor areas of the brain (Rizzolatti et al., 2001; Cross et al., 2009) and this activation is thought to represent a simulation process such that predicting action outcomes of observed actions is possible (Blakemore & Decety, 2001; Knoblich, 2008; van der Wel et al., 2013). Participants in Experiment 3 observed a portion of single dart throws and attempted to predict if the dart throw landed in the yellow goal area of the target. The action prediction task was completed both before and after an observation phase. In the observation phase, participants viewed the expert video from Experiments 1 and 2. Presumably, the action simulation process occurred during the observation of this video. The nature of the simulation process posited to occur during action observation is ambiguous. The direct matching theory would predict that simulation is effector-dependent (Rizzolatti et al., 2001). In the case of observing dart throwing, the limb exhibiting the most movement is the throwing arm. If action simulation is indeed effector-dependent and reliant on the motor system being available, preoccupying the arms with an unrelated motor task during action observation should disrupt the simulation process. In Experiment 3, participants' motor systems were either not preoccupied or were actively or passively preoccupied by use of pedaling a mini bike. In two of the four experimental conditions, participants were required to actively pedal the mini bike during the observation phase. If action simulation is effector-dependent, then actively *hand* pedaling the mini bike during the observation of the expert dart throwing model should inhibit the observer's ability to simulate. However, this should not be the case if participants are actively pedaling the mini bike with their feet, as the throwing arm in observed dart throwing is the most visually dynamic limb. If action simulation is effector-dependent, then one would expect that participants who actively pedal the mini bike with their hands should demonstrate the smallest improvement in their action prediction abilities from before to after the observation phase.

The action reconstruction theory would predict that action simulation occurs at a higher representative level than the direct matching theory. It has been suggested that the role of the MNS (or more generally the action observation network) is to represent observed actions at the goal level (Thornton & Knoblich, 2006). In other words, the action reconstruction theory would suggest that action simulation is reliant on action planning. Active and passive movements differ cognitively because active movements require action planning while passive movements do not (Hecht et al., 2001). If the simulation of observed actions results in the ability to correctly predict action outcomes, would passive motor movements made during action observation interfere with action prediction abilities? To address this question, in the observation phase of Experiment 3, one group of participants were passively pedaled by the mini bike. If action simulation is reliant on action planning, participants who were passively pedaled by the mini bike, and therefore not engaged in action planning during action observation, should enhanced abilities to predict the landing locations of dart throws after the observation phase. Conversely, participants who actively pedal the mini bike with their hands or their feet should demonstrate little change in the action prediction tasks from before to after the observation phase, as in both cases these participants are actively planning their actions during the observation of the dart throwing model.

4.1.2 Methods.

Participants. 121 Rutgers University – Newark undergraduate students (mean age = 20.83 years, 79 females and 31 males) participated for partial course credit. All of the participants were right handed and had normal or corrected to normal vision. None of the participants had any dart throwing experience. Of the initial 121 participants, 32 were eliminated from the statistical analyses because they performed either below chance in the pre-action prediction task, below chance in the post-action prediction task or at chance in both the pre- and post-action prediction tasks. The resultant group of participants used in the final statistical analyses contained 89 participants (mean age = 20.81 years, 61 females and 28 males).

Materials. The experiment consisted of three parts: the pre-action prediction task, an observation phase with a motor manipulation, and the post-action prediction task. Participants' judgments in the pre- and post-action prediction task were captured using E-prime 2.0 software (Psychological Software Tools, Inc.) running on an iBuyPower computer with an 22" diagonal Sceptre monitor (60 Hz, 1680 x 1050 pixel resolution)positioned approximately 61cm away from each participant.

The key motor manipulation employed the use of a mini bike during the observation phase. The Sunny Health and Fitness mini bike is often used for stroke patients to help in rehabilitation. Settings on the mini bike allowed users to pedal with their own force or with help of the motor. The mini bike includes straps that fit users' hands and feet (Figure 23). The expert video used in Experiments 1 and 2 was viewed during this observation phase and was controlled by Media Player Classic – Home Cinema software.

At the conclusion of the experiment, participants filled out an Action Observation Survey. This survey was created specifically for this experiment for the purpose of examining individual differences amongst participants in their self-reported experience throughout the experiment. The survey contains nine questions assessing the participant's confidence level in his or her responses and his or her subjective experiences during the motor manipulation. For example, one question asked with how much force they used when pedaling the mini bike during the observation phase. Finally, an open-ended question was included at the end to determine what visual information participants used to respond in the pre- and post-action prediction task. A copy of the Action Observation Survey can be found in Appendix A.

Figure 23. Photographs of the mini bike used for the motor manipulations in Experiment 3. Participants either actively or passively performed hand pedaling or active feet pedaling during the observation phase.

Pilot testing for action prediction video clips. In the pre- and post-action prediction tasks in Experiment 3 and 4, participants were required to make judgments about dart throwing outcomes. Specifically, participants predicted whether each model's dart throw would result in the dart landing in the yellow goal area of the target (hit) or landing outside of the yellow goal area (miss). The video clips began before the model lifted his hand to throw the dart and ended before the dart landed on the target.

The raw footages of the expert and novice dart throwing models from Experiments 1 and 2 were edited to create the individual dart throwing stimuli for the pilot testing of the action prediction video clips. First, a research assistant coded each individual dart throw from the expert and novice video clips as clearly landing or not landing in the yellow goal area. If the dart did not land in the yellow goal area, the research assistant coded which colored ring the dart landed in (see Figure 1 for a picture of the target). Then, the raw footage was edited (Adobe Premiere Pro v2.0) to isolate dart throws that resulted in "hits", or dart throws that clearly landed in the yellow goal area. Additionally, the raw footage was edited to isolate dart throws that resulted in "misses", or dart throws that clearly did not land in the yellow goal area. For the pilot testing, the individual video clips coded as "misses" included darts that landed in the blue, black, and white rings, as well as darts that missed the target completely. Dart throws that landed in the red rings of the target were excluded based on the assumption that these throws may be too close to the yellow goal area to allow for visual discrimination.

A group of 12 naïve volunteers (graduate students and research assistants from the Rutgers-Newark Psychology Department) viewed several types of video clips to determine the best way to design the pre- and post-action prediction task. The video clips began as the model lifted his arm and ended before the dart landed on the target. As an example, Figure 24 shows the last depicted frame of the expert model throwing a dart at the target. This figure illustrates that the video ended before the dart reached the target. As a result, observers were required to extrapolate the future trajectory of the dart in order to determine each dart's likely landing location. During this pilot testing period, volunteers viewed each clip once and reported after each clip whether the dart, if it continued on its current trajectory, would hit or miss the yellow goal area of the target. After each response, the next video clip was shown.

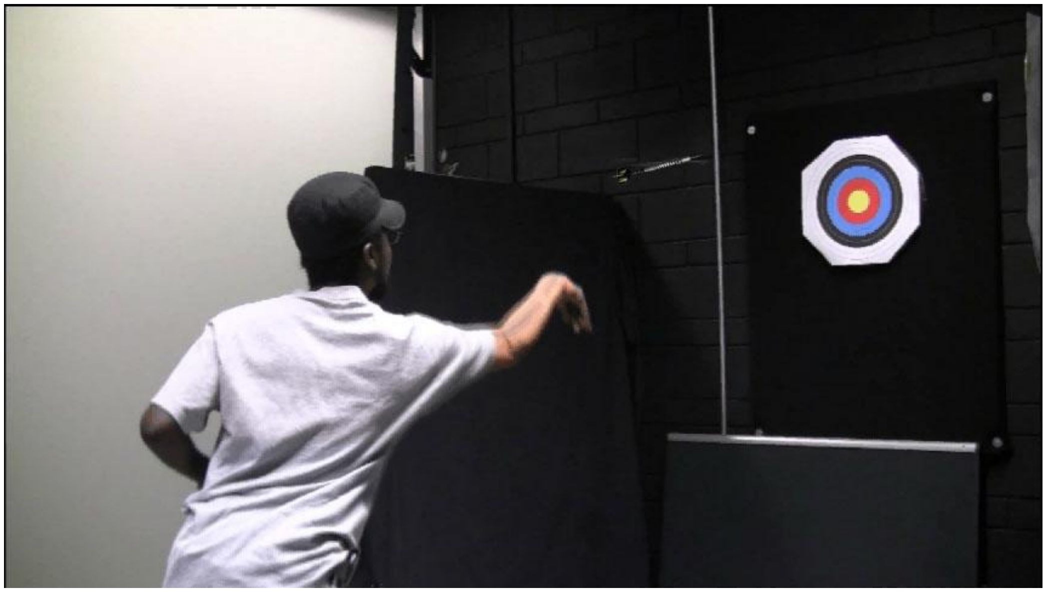


Figure 24. The last frame of video depicting a single dart throw by the expert dart throwing model. The model is standing approximately 7'9" away from the target and is viewed from a ¾ point of view.

Based on the inconclusiveness of the results of Experiments 1 and 2, we first investigated in this pilot testing phase if observers could better detect dart throwing outcomes from the novice or expert dart thrower. Ten clips (5 hits, 5 misses) from the novice dart thrower and ten clips from the expert dart thrower (5 hits, 5 misses) were created, each clip lasting 2000ms long. On average, the volunteers correctly predicted the landing locations of the darts on 43% of the novice model's throws and on 62% of the expert model's throws. Clearly, action prediction was superior during the observation of expert dart thrower. This lead to the decision to show only videos depicting the expert dart thrower during the pre- and post-action prediction task employed Experiments 3 and 4.

A single dart throw occurs extremely quickly, and as such video clip duration was also manipulated for pilot testing. Volunteers viewed both 2000ms and 3000ms video clips of the expert dart thrower. The timing of the expert's individual dart throws naturally varied in length (from the point the model lifted his arm to before the dart landed on the target) but averaged to be approximately 1000ms long. To create 2000ms and 3000ms clips from the naturally varying raw footage and to ensure that stimulus duration in the action prediction task was constant, the last frame of each video clip was presented statically to equate the stimuli duration. The 2000ms and 3000ms video clips the volunteers viewed here only differ in the amount of time the last frame was presented statically. The 12 volunteers observed 20 video clips (half 2000ms clips, half 3000ms clips; half hits and half misses) and verbally responded whether the dart would hit or miss the yellow area of the target. Accuracy for the 2000ms and 3000ms video clips was similar, 53% accuracy and 59% accuracy respectively. The difference in accuracy between the 2000ms and 3000ms video clips was minimal and to avoid a potential confound of participants using the trajectory of the dart during the action prediction task, we decided to only include 2000ms clips.

The accuracy for 2000ms expert video clips was poor (53% average accuracy) and it is possible that seeing each dart throw only once rendered the task too difficult for observers. Therefore, in a subsequent manipulation, each video clip was displayed either once (2000ms) or three times sequentially (6000ms). As before, half of the dart throws were “hits” (dart would have continued into the yellow bull’s eye) and half were “misses”. Action prediction accuracy was 51.3% in the 6000ms condition (each throwing action shown three times) and 56.1% in the 2000ms condition. Because showing a dart throw three consecutive times does not appear to improve accuracy significantly, the stimuli for the pre- and post- action prediction task only included a single dart throw shown once (2000ms condition).

To ensure that participants in Experiments 3 and 4 remained motivated to perform the action prediction task, 2000ms video clips from the expert model were selected for accuracy levels above chance based on the volunteers’ results. From all of the pilot tested expert video clips, 15 clips resulting in hits and 15 clips resulting in misses were selected in which the average accuracy was between 71 - 74%. The selected “hit” video clips had an overall accuracy of 71.9% and the selected “miss” video clips had an overall accuracy of 74.1%. In the final version of the action prediction task, each of these 30 selected videos was presented three times for a total of 90 trials.

Design. All of the participants in Experiment 3 performed in the three experimental parts: the pre-action prediction task, the observation phase with a motor manipulation, and the post-action prediction task (Figure 25). The participants were randomly assigned to one of the four possible experimental motor conditions during the observation phase in this between-subjects design.

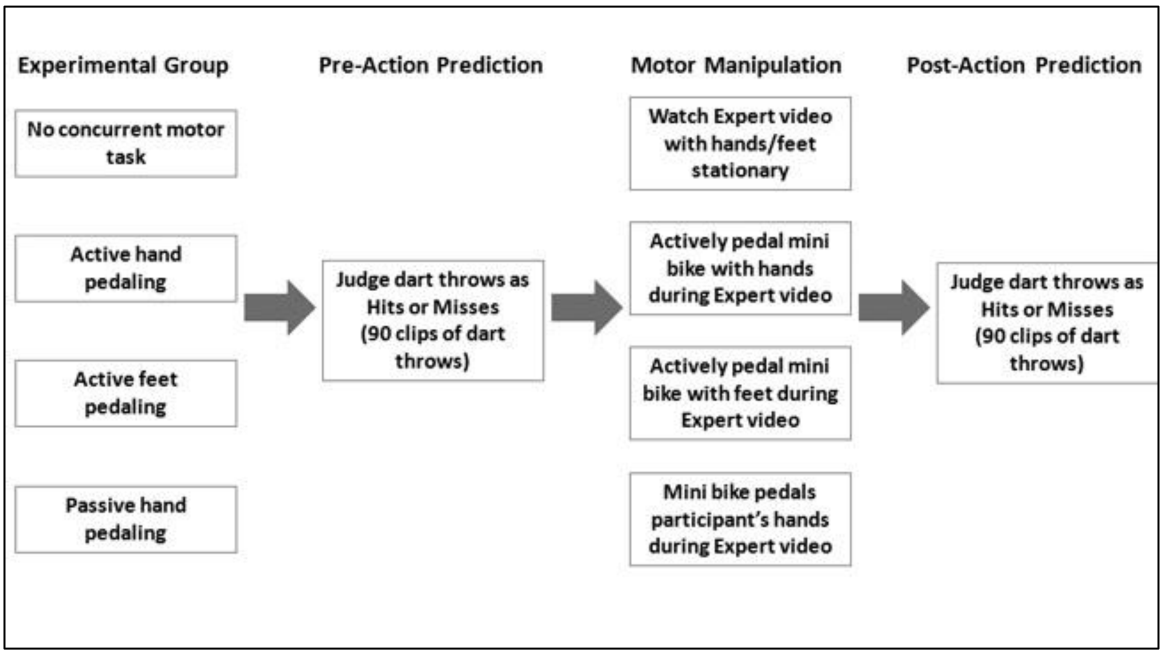


Figure 25. Experiment 3 design. Participants were randomly assigned to one of four different motor manipulations during the observation of the expert model video. All of the participants completed the pre-action prediction task, followed by the observation phase, and finally the post-action prediction task.

Procedure. First, all participants performed the 2AFC pre-action prediction task. During the pre-action prediction task, all of the participants were seated approximately 61cm away from the computer screen. The participants completed six practice trials and 90 randomly presented experimental trials. On each trial, participants viewed a fixation cross for 500ms followed by a unique dart throw lasting 2000ms. Then, participants responded with a button press if the dart would have “hit” or “missed” the yellow target area. The pre-action prediction task lasted approximately 10 minutes.

Following the pre-action prediction task, all of the participants completed the observation phase in which they observed the same expert video from Experiments 1 and 2 on the computer screen from approximately 61cm away. Before the observation of the expert video, participants were asked to observe the model’s movement and the outcome of each dart throw in order to report at the conclusion of the video how many times the model threw darts into the yellow goal area. At the conclusion of the expert video, participants reported as accurately as possible the number of darts landing in the yellow goal area to encourage attentiveness to the video. While all of the phases of Experiment 3 involve observation of the model to some degree, the observation phase with the motor manipulations is the only phase in which participants saw the outcome of the individual dart throws. In the pre- and post-action prediction task, participants were not given feedback on their performance as to ensure that any differences from the pre- to post-action prediction task were due to the experimental manipulation.

Based on the randomly assigned experimental conditions, participants watched the expert video during the observation phase while at the same time (1) holding the pedals of the mini bike and keeping still, (2) actively pedaling the mini bike with their hands, (3) actively pedaling the mini bike with their feet, or (4) their hands were passively pedaled by the mini bike’s motor. During the observation phase, participants who were instructed to observe the expert video with no concurrent motor task simply placed their palms on the pedals of the mini bike. Participants in the active hand pedaling condition placed their hands in the straps connected to the pedals of the mini bike before the observation of the expert video and began pedaling the mini bike at a constant, comfortable speed throughout the observation period. Participants in the active feet pedaling condition placed their feet into the straps connected to the pedals of the mini bike before observation of the expert video and pedaled the mini bike at a comfortable, constant speed during the entire observation phase. For participants in the passive condition, whose hands were pedaled by the motorized mini bike, the mini bike's motor was set at a moderate speed and participants were instructed not to use their own force to move the pedals but to relax and let their hands move passively with the pedals of the mini bike throughout the observation phase. Participants were asked to confirm if their arms felt like "jelly" before starting the expert video as a way to check if they were passively being pedaled. After the observation phase, all of the participants from each of the experimental conditions performed the same post-action prediction task. The experimental procedure of the post-action prediction task and the stimuli presented were the same as the pre-action prediction task. However, the presentation order of the individual dart throwing stimuli was randomized to eliminate potential sequence effects. Finally, all of the participants completed the Action Observation Survey (see Appendix A). The entire experiment lasted approximately 35 minutes.

4.1.3 Results.

Given the 2AFC design of the pre- and post-action prediction tasks, the data were analyzed using signal detection theory (MacMillan & Creelman, 1991). Of importance to the current study and Experiment 4, d-prime was examined. D-prime (d') is a measure of perceptual sensitivity and is calculated by subtracting the rate of false alarms (incorrectly responding that the individual dart throw landed in the yellow goal area when in reality it did not) from the rate of hits (correctly responding that the individual dart throw landed in the yellow goal area). A higher d-prime score indicates a larger perceptual sensitivity to differences in the stimuli as hits or misses. Furthermore, correct percentages were calculated for video clips that would result in hits, misses above the yellow goal area (high misses), and misses below the yellow goal area (low misses). These results are reported in percentages, in which 100% means correctly identifying a video resulting in a hit, high miss or low miss perfectly every time. The results for average d' score, average percent correct for video clips that would have resulted in hits, high misses and low misses in the pre- and post-action prediction task sorted by experimental group can be seen in Table 28.

Pre-action prediction task. Before the introduction of the motor manipulation during the observation phase, several one-way ANOVAs were conducted to determine if the experimental groups differed from one another or if they performed similarly in terms of d' and percent correct. For average d' scores in the pre-action prediction task, the experimental group performed equivalently (F (3, 85) = .617, p = .606, n_p^2 = .021). The participants showed no differences for performance in the pre-action prediction task in the percentage correct for action prediction clips that would result in hits (F (3, 85) = .013, p = .998, n_p^2 = .000), high misses (F (3, 85) = 1.391, p = .251, n_p^2 = .047), and low misses (F (3, 85) = .087, p = .967, n_p^2 = .003). These analyses ensure that any differences amongst the experimental groups in the post-action prediction task following the manipulation is likely due to the manipulation itself.

Condition	d' Before	d' After	% Correct Hits Before	% Correct Hits After	% Correct High Miss Before	% Correct High Miss After	% Correct Low Miss Before	% Correct Low Miss After
No Motor	**1.137** (SE=.12)	**2.189** (SE=.38)	**69%** (SE=.03)	**83%** (SE=.03)	**64%** (SE=.04)	**58%** (SE=.05)	**77%** (SE=.03)	**79%** (SE=.04)
Active Hands	**1.259** (SE=.17)	**1.883** (SE=.21)	**70%** (SE=.03)	**84%** (SE=.02)	**65%** (SE=.05)	**66%** (SE=.05)	**79%** (SE=.05)	**79%** (SE=.05)
Active Feet	**1.388** (SE=.12)	**1.786** (SE=.15)	**70%** (SE=.03)	**73%** (SE=.03)	**76%** (SE=.04)	**76%** (SE=.05)	**79%** (SE=.05)	**87%** (SE=.03)
Passive Hands	**1.467** (SE=.27)	**2.00** (SE=.21)	**70%** (SE=.03)	**83%** (SE=.02)	**69%** (SE=.05)	**70%** (SE=.05)	**76%** (SE=.05)	**83%** (SE=.04)

Table. 28. The average d' scores and percent correct for video clips that would have resulted in hits, misses high and low by the four experimental conditions. The higher d' score observed, the greater visual sensitivity to the dart throwing clips. Percent correct for clips resulting in hits, high or low misses are presented in percentages.

Performance before and after the observation phase. Performance in the pre- and post-action prediction tasks were examined with a series of mixed model ANOVAs in which the between-subjects variable is the motor preoccupation condition during the observation phase and d' and percentage correct for video clips resulting in hits, high and low misses in the pre- and post-action prediction tasks are the within-subjects variables. The results of the mixed model ANOVA for d' can be found in Table 29.

	Main Effect of Time (before/after)	**Main Effect of Group (mini bike condition)**	**Interaction of Time * Group**
F-test on d' scores	F(1, 85) = 28.056, ***p* = .000**, n_p^2 = .248	F(3, 85) = .175, *p* = .913, n_p^2 = .006	F(3, 85) = 1.277, *p* = .287, n_p^2 = .043

Table 29. Results from the 4 (experimental condition) x 2 (before and after performance) mixed model ANOVA for d' scores. The between-subjects variable is the motor preoccupation condition and the within-subjects variable is the average d' scores before and after the manipulation.

For average d' scores, the mixed model ANOVA revealed a significant main effect of time (F (1, 85) = 28.056, *p* = .000, n_p^2 = .248), such that performance, as indicated by higher d' scores, was better in the post-action prediction task as compared to the pre-action prediction task. As can be seen in Figure 26, all of the participants in each of the experimental groups improved from the pre- to post-action prediction task in terms of d' scores. There were no other significant main effects or interactions (*p* > .05).

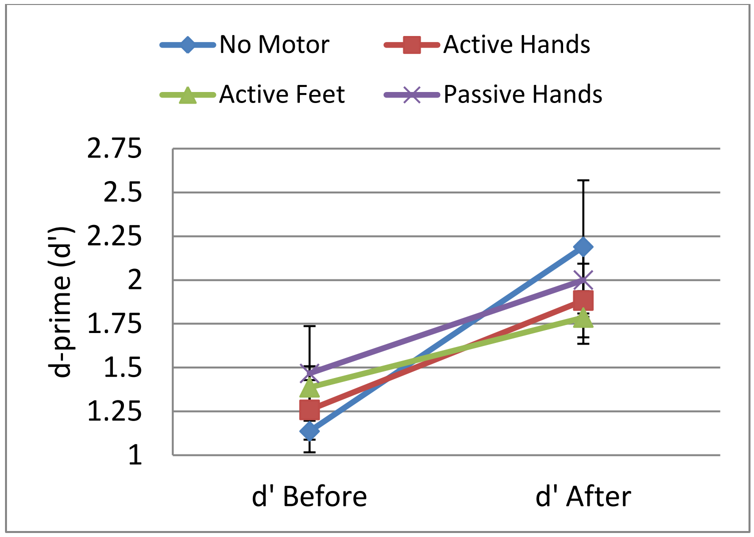


Figure 26. The average d’ scores before (pre-action prediction task) and after (post-action prediction task) the observation phase with motor manipulations by experimental condition.

To examine the magnitude of changes in d’ from before to after the manipulation during the observation phase, a difference score was created by subtracting the d’ scores in the post-action prediction task from the d’ scores in the pre-action prediction task. The resultant d’ change variable reveals shifts in d’ over the course of the experiment such that a positive score demonstrates improvement from the pre- to post action prediction tasks, while a negative score indicates a decline in performance. Figure 27 shows the amount of change in d’ over the course of the experiment by experimental group. Again, this figure demonstrates that all of the experimental groups improved in visual sensitivity from the pre- to post-action prediction task and there were no significant differences amongst the groups (F (3, 85) = 1.277, p = .287, n_p^2 = .043). Participants in the No Motor manipulation condition showed the greatest improvement, as illustrated by the largest positive change in d’ scores. Participants in the other experimental conditions showed less change, albeit improvement in d’ scores overall.

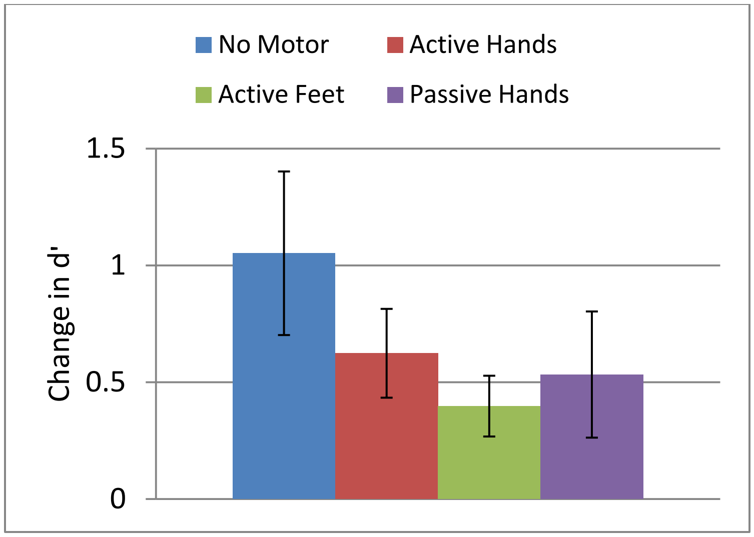


Figure 27. The change in average d' scores before (pre-action prediction task) and after (post-action prediction task) the observation phase with motor manipulations by experimental condition. Positive scores indicate improvement from the pre- to post-action prediction tasks, while negative scores indicate decline in performance.

The results from the mixed model ANOVA for the average percentage correct of video clips resulting in hits can be found in Table 30.

	Main Effect of Time (before/after)	**Main Effect of Group (mini bike condition)**	**Interaction of Time * Group**
F-test % Correct for Hits	F(1, 85) = 47.099, ***p* = .000**, n_p^2 = .357	F(3, 85) = 1.381, *p* = .254, n_p^2 = .046	F(3, 85) = 2.295, ***p* = .084**, n_p^2 = .075

Table 30. Results from the 4 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percentage correct for "hit" clips. The between subjects variable is the motor preoccupation condition and the within subjects variable is the average percent correct before and after the manipulation.

For the percentage correct of "hit" clips, the mixed model ANOVA showed a significant main effect of time (F (1, 85) = 47.099, *p* = .000, n_p^2 = .357) such that participants overall were more correct after the manipulation in the post-action prediction task than before. Additionally, there was a marginally significant interaction between time and experimental group (F (3, 85) = 2.295, *p* = .084, n_p^2 = .075). Figure 28 shows the average percentage correct for video clips resulting in hits by each experimental group both before (pre-action prediction task) and after (post-action prediction task) the manipulation. Post hoc tests did not reveal significant differences between the average percent correct of participants in the different experimental conditions. However, a closer look at Figure 28 shows that participants in the Active Feet condition showed no change for "hit" clips from the pre- and post-action prediction tasks. Participants in all of the other experimental conditions showed improved percentages for video clips resulting in hits. There were no other significant main effects (p > .05).

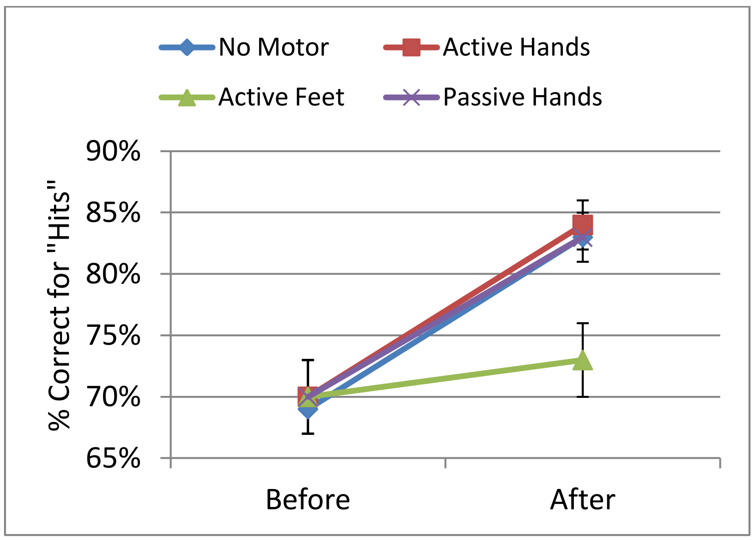


Figure 28. The average percent correct for "hit" video clips before (pre-action prediction task) and after (post-action prediction task) the observation phase with motor manipulations by experimental condition.

The results for the mixed model ANOVA on the average percentage correct of video clips resulting in misses above the yellow goal area (high misses) can be found in Table 31. A mixed model ANOVA on the percentage correct of high misses from pre- to post-action predictions tasks by experimental group presented a marginally significant main effect of group (F (3, 85) = 2.698, p = .051, n_p^2 = .087). Post hoc tests revealed a significant difference between the participants in the No Motor condition and the Active Feet condition (F (3, 85) = 2.698, p = .047). Specifically, the participants in the Active Feet condition performed more correctly in the post-action prediction task than participants in the No Motor condition (see Figure 29). While participants in the No Motor condition demonstrated a decline in performance for action prediction clips resulting in high misses over the course of the experiment, participants in the other three experimental conditions showed consistent performance in the pre- and post-action prediction tasks. There were no other significant main effects or interactions ($p > .05$).

	Main Effect of Time (before/after)	**Main Effect of Group (mini bike condition)**	**Interaction of Time * Group**
F-test % Correct for High Misses	$F(1, 85) = .191$, $p = .663$, $\eta_p^2 = .002$	$F(3, 85) = 2.698$, $\mathbf{p = .051}$, $\eta_p^2 = .087$	$F(3, 85) = .303$, $p = .823$, $\eta_p^2 = .011$

Table 31. Results from the 4 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percent correct for video clips resulting in misses above the yellow goal area. The between subjects variable is the motor preoccupation condition and the within subjects variable is the average percentage correct before and after the manipulation.

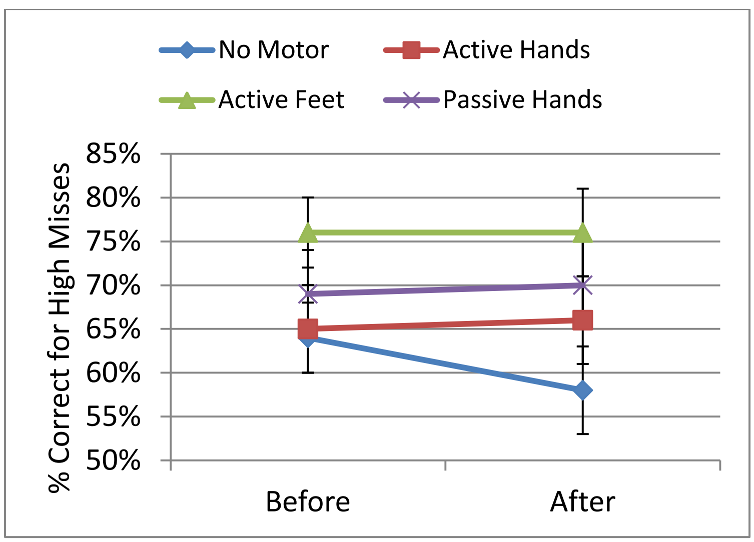


Figure 29. The average percent correct for "high miss" video clips before (pre-action prediction task) and after (post-action prediction task) the observation phase with motor manipulations by experimental condition.

Lastly, the results for the mixed model ANOVA for the average percentage correct of video clips resulting in misses below the yellow goal area (low misses) before (pre-action prediction task) and after (post-action prediction task) the observation phase and experimental manipulation by group revealed a significant main effect of time (F (1, 85) = 4.647, *p* = .034, n_p^2 = .052) (see Table 32). As can be seen in Figure 30, overall participants showed improved correct percentages for video clips resulting in misses below the yellow goal area from the pre- to post-action prediction task. The main effect of time and the interaction between time and experimental group did not reach significance (*p* > .05).

	Main Effect of Time (before/after)	**Main Effect of Group (mini bike condition)**	**Interaction of Time * Group**
F-test % Correct for Low Misses	F(1, 85) = 4.647, ***p* = .034**, n_p^2 = .052	F(3, 85) = .302, *p* = .824, n_p^2 = .011	F(3, 85) = .925, *p* = .432, n_p^2 = .032

Table 32. Results from the 4 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percent correct for video clips resulting in misses below the yellow goal area. The between subjects variable is the motor preoccupation condition and the within subjects variable is the average percentage correct before and after the manipulation.

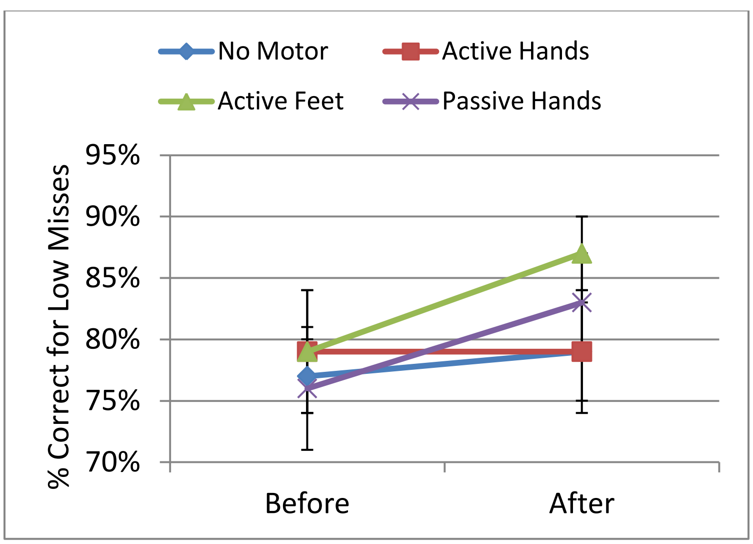


Figure 30. The average percent correct for “low miss video clips before (pre-action prediction task) and after (post-action prediction task) the observation phase with motor manipulations by experimental condition.

Self-report measures and changes in visual sensitivity to action prediction. During the observation phase with motor system preoccupation manipulations, participants were asked to report the number of times the expert dart throwing model in the observation video hit the yellow goal area. Initially, participants were instructed by the experimenter to attend to the model's dart throwing actions and the outcome of each dart throw to ensure attention was being paid to the video during the observation phase. During data analysis, the self-reported number of times the model hit the yellow goal area of the target in the observation phase of the expert model was positively correlated with change in d' scores overall for the participants (r = .318, p = .002). In other words, the more accurate participants were at reporting the number of times the model hit the goal area during the observation phase (regardless of the motor preoccupation manipulation), the greater that participant's change in d' from the pre- to post-action prediction tasks (see Figure 31). A simple linear regression analysis was used to examine if the self-reported number of hits during the observation phase significantly predicted change in d' scores from the pre- to post-action prediction tasks. The results of the regression indicate that the predictor variable (reported number of hits) explains 10% of the variance (R^2 = .101, F (1, 87) = 9.089, p = .002). For every unit of increase in reported number of hits during the observation video, change in d' scores increased .044 units (β = .044, p = .002).

One potential issue with the Pearson's correlation analysis above is that certain experimental groups may have reported significantly less accurate numbers because their motor activity distracted them from observing the expert model. A one-way ANOVA was conducted to determine if the experimental groups differed in the average number of self-reported hits observed during the observation video. The results demonstrated a significant difference between the groups (F (3, 85) = 4.094, p = .009, n_p^2 = .126) such that participants in the Active Feet condition reported the least accurate number of hits (mean = 44.09 hits) as compared to the No Motor condition (mean = 52.10 hits, F (3, 85) = 4.094, *p* = .008) and the Passive Hands condition (mean = 50.26 hits, F (3, 85) = 4.094, *p* = .053). However, it is important to note that the average number of hits reported by participants in the Active Hands condition did not differ significantly from participants in the No Motor or Passive Hands conditions, suggesting that active pedaling is not simply distracting.

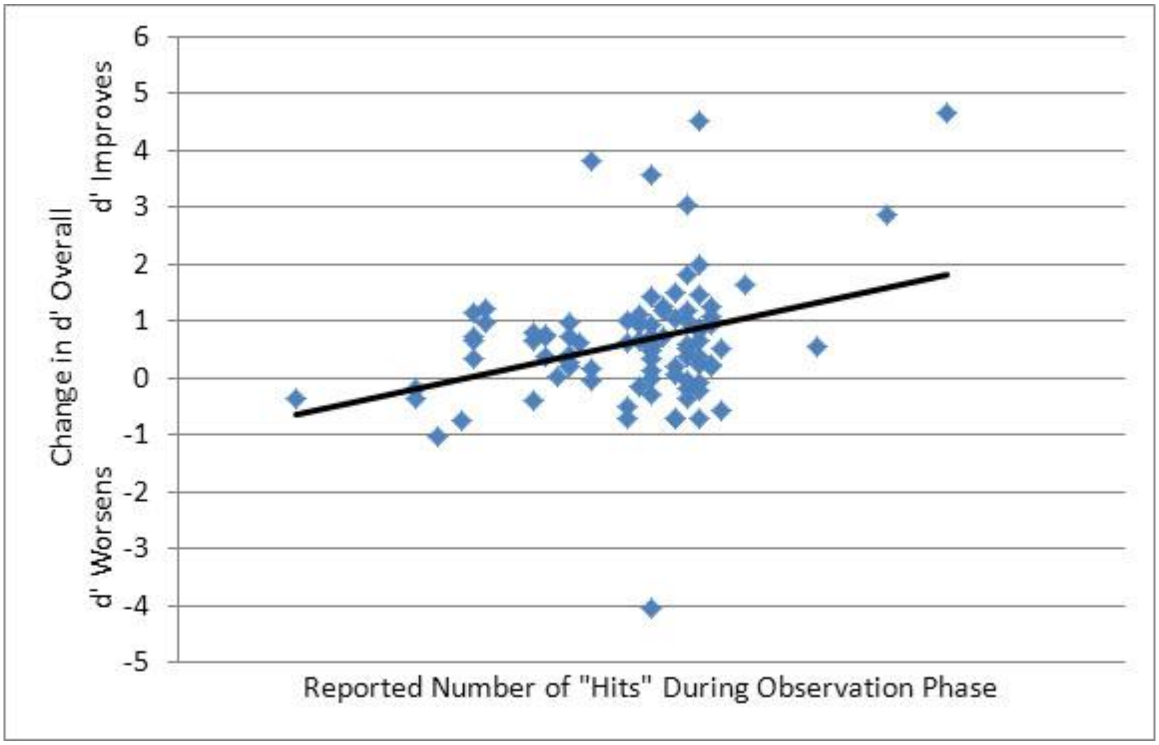


Figure 31. Correlation between the self-reported number of times the expert model hit the yellow goal area during the observation video and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) by experimental manipulation.

At the conclusion of the experiment, participants filled out the Action Observation Survey (see Appendix A for a full version). These questions were designed to ask participants to report their subjective experience throughout the experiment. Specifically of interest in data analysis, question #7 read, "While using the mini bike, how much force were you using to move the pedals?". Participants could answer on a scale of 1 (no force at all) to 5 (a great deal of force). The self-reported amount of force used to move the pedals of the mini bike was negatively correlated with changes in d' scores (r = -.263, p = .018). In other words, the more self-reported effortful force participants exhibited on the mini bike during the observation phase, the less change in d' scores observed from the pre- to post-action prediction tasks (see Figure 32). A simple linear regression analysis was used to test if the reported force with which a participant pushed the pedals of the mini bike significantly predicted change in d' scores from the pre- to post-action prediction tasks. The results of the regression indicated that the predictor variable (self-reported force) explains 7% of the variance (R^2 = .069, F (1, 79) = 5.883, p = .018). For every unit of increase in self-reported force, change in d' scores decreased .315 units (β = -.315, p = .018).

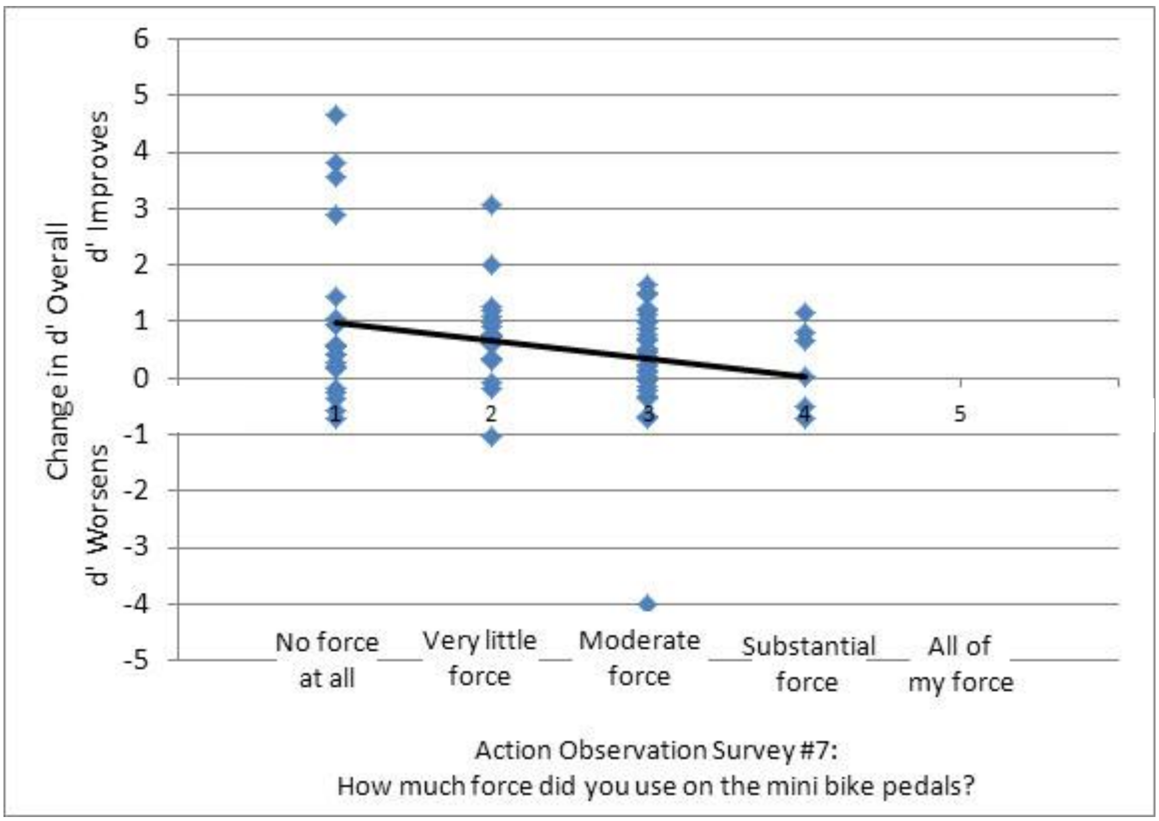


Figure 32. Correlation between the self-reported amount of force used on mini bike during the observation phase and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) the experimental manipulation.

Finally, the Action Observation Survey included an open-ended question asking participants to report what lead them to respond “hit” or “miss” following the action prediction video clips. Specifically, question #9 reads, “What about the video informed you whether the dart throw would hit or miss the yellow area?”. Based on the answers from the participants overall, one of three things informed responses. Participants used the dart’s location or trajectory, the model’s arm or wrist movements, or a combination of the both the dart and model’s arm movement. The results showed that 52 participants used the dart’s movements or trajectories alone, 11 participants used the model’s arm movement alone, and 16 participants used a combination of both the dart and model’s arm movement. A potential problem with the design of this study is that participants could use information specific to the dart trajectory to respond (although they do not see the outcome of the dart throw) and improve at the action prediction task above and beyond that of participants using the model’s arm movement or a combination of visual information. A one-way ANOVA was conducted to determine if there were differences in d’ scores from the pre- to post-action prediction task based on how participants responded to question #9. Using the type of response as the grouping variable, the results showed no differences amongst the type of visual information participants used to respond (dart alone, model alone, or both) and changes in d’ scores ($F(2, 76) = .274$, $p = .761$, $n_p^2 = .007$). Although the majority of participants in this study self-reportedly used the dart’s trajectory as a cue to respond, this lead to no observable advantages compared to participants who used other visual information.

4.1.4 Discussion.

The overarching goal of Experiment 3 was to better characterize the simulation process theoretically initiated by action observation and the influences of action simulation on predicting action outcomes. Participants completed the pre- and post-action prediction tasks in which partial dart throws were observed and participants judged if the dart throw would have resulted in a “hit” or “miss”. In between the pre- and post-action prediction tasks, participants observed the expert model performing dart throwing in the observation phase. Importantly, although all phases of this experiment involved observation, it was only during the observation phase that participants saw the outcome of the model’s action. To understand the nature of the simulation process thought to be occurring during the observation phase, a mini bike was employed simultaneously in various ways. Participants actively pedaled the mini bike with their hands, actively pedaled the mini bike with their feet, were passively pedaled by the mini bike, or did not pedal the mini bike at all. If action simulation during action observation is effector-dependent, as would be predicted by the direct matching theory, that action simulation should be disrupted by actively pedaling the mini bike with the hands, but not the feet. This potential disruption in action simulation should interfere with participants’ ability to correctly predict action outcomes. However, if action simulation is reliant on areas of the action observation network related to action planning, as predicted by the action reconstruction theory, that action simulation should be disrupted by actively pedaling the mini bike with the hands and feet, but not passive pedaling.

Despite our initial hypotheses, the results of Experiment 3 did not provide strong support for either the direct matching theory (Rizzolatti et al., 2001) or the action reconstruction theory (Csibra, 2008). The experimental groups revealed no significant differences in changes of visual sensitivity to predicting dart throwing outcomes. While participants in the No Motor condition exhibited the greatest change in d’ from the pre- to post-action prediction task as was initially predicted, this amount of change was not significantly different from the other groups. Furthermore, the results showed that overall each experimental group improved for video clips that would results in a hit or low miss based on correct percentages. This suggests that with visual exposure to the model’s movement patterns and action outcomes during the observation phase, participants were better able to discriminate dart throws that would hit the yellow rings of the target or land below the yellow rings. Interestingly, there was no main effect of time for dart throws that would results in a high miss. Even with visual training during the observation phase, participants did not learn to differentiate misses that landed above the yellow goal area, suggesting this type of dart throw was more difficult to classify overall. The results also showed that participants in the Active Feet condition were best at discriminating the high miss video clips, however, this group showed no change in percentage correct from the pre- to post-action prediction tasks. Taken together, all of the participants demonstrated improvement in the post-action prediction task as compared to the pre-action prediction task regardless of the motor preoccupation condition in which they were assigned.

The direct matching theory would predict that simulation is effector-dependent (Rizzolatti et al., 2001). In the case of dart throwing, the most visually dynamic limb is the arm. Although participants in the Active Hands condition showed less improvement in visual from the pre- to post-action prediction tasks as compared to participants in the no motor condition, this difference was not significant. Furthermore, participants in the Active Feet condition also showed a similar pattern of results. The action reconstruction theory (Csibra, 2008) suggests that representations of observed actions first occur at a higher level than the direct matching theory. In turn, action planning during action observation should interfere with the simulation process. However, our results show that participants in the passive hands condition were no different in visual sensitivity or accuracy during the pre- and post-action prediction tasks from the other experimental conditions.

The action observation network (Cross et al., 2009) encompasses a large network of brain areas related to action observation and action execution (Cross et al., 2009). It has been previously reported that these brain areas reveal differentiated activation patterns to action goals as compared to action kinematics (Hamilton & Grafton, 2006; Kilner & Lemon, 2013). Although we attempted to explore the specific characteristics of the simulation process through the lens of the direct matching and action reconstruction theories, it appears as though the three types motor input employed in Experiment 3 during action observation disrupts simulation to some degree. It is not clear, however, if any type of motor input during action observation disrupts simulation. For example, perhaps other types of motor activity (e.g., throwing an object) concurrently performed during action observation would differentially influence one's subsequent ability to predict dart throwing outcomes. Furthermore, brain activations to observed action goals and observed action kinematics may differ but motor input during observation may affect these areas of the action observation network similarly.

In line with previous work on changes in visual discrimination through visual training, participants in Experiment 3 demonstrated learning in the action prediction task, as evidenced by improved visual sensitivity and accuracy in the post-action prediction task. Grossman and colleagues (2004) showed that with visual training and practice, participants could accurately detect human point-light figures in a mask. This visual training transferred to novel human point-light movement that participants were not previously trained on. Similarly, Jastorff and colleagues (2006; 2009) provided evidence for visual learning of human and novel nonhuman forms. In the 2AFC discrimination task, participants viewed two point-light figures simultaneously and were asked to judge if the second stimulus matched the first stimulus. Half of the stimuli were point-light human figures and the other half of the stimuli were point-light "creatures". In both studies, participants were able to accurately discriminate the human point-light figures and the "creature" point-light figures with visual training (Jastorff et al., 2006; 2009). Experiment 3 extends the current knowledge of visual training on discrimination of complex human movement by revealing that visual training can improve sensitivity to a complex, ecologically valid motor task.

Our results suggest that one does not need to be an elite athlete to discriminate complex movement patterns associated with a particular sport. Previous research has shown that athletes outperform novices in the visual discrimination tasks related to their sport (Jackson et al., 2006; Canal-Bruland & Schmidt, 2009; Canal-Bruland et al., 2010; Wright et al., 2010; Calvo-Merino et al., 2005, 2006, 2010; Farrow & Abernathy, 2003; Mann et al., 2010; Sebanz & Shiffrar, 2009, Hohmann et al., 2011; Aglioti et al., 2008). A question of debate, however, is whether this superior visual discrimination observed in athletes is the result of motor experience and/or visual experience. Many of these studies suggest that motor experience drives the visual discriminative abilities in athletes as compared to novices, however, Aglioti and colleages (2008) demonstrated that visual experience may also play a role in action observation. Basketball coaches (visual experts) showed similar motor priming during observation of free throw shots as elite basketball players showed. The results from Experiment 3 provide evidence that novices in these studies, with visual training, could improve their ability to visual discriminate complex movements from various sports. Related to the effects of visual training on discrimination of complex movements, in Experiment 3 participants following the observation phase were asked to report the number of times the expert model hit the yellow goal area. A Pearson's correlation found that the more accurate participants were at reporting the number of hits, the greater observed change in visual sensitivity from the pre- to post-action prediction tasks. This suggest that the more attentive participants were to crucial elements of the expert dart throwing video, the more visually sensitive and accurate participants were to video clips in the post-action prediction task.

One of the most interesting and surprising findings from Experiment 3 involves the role of physical effort on action simulation and predicting action outcomes. Following the post-action prediction task, participants filled out the Action Observation Survey. One particular question of interest asked participants to self-report the amount of force with which they pedaled the mini bike during the observation phase. A Pearson's correlation revealed that the more self-reported force participants pedaled the mini bike with, the less observed change in visual sensitivity from the pre- to post-action prediction tasks. Although we observed no significant differences amongst our experimental groups, this correlation is in line with our predictions about action simulation during the observation phase. If the motor system is engaged in an unrelated motor task during action observation, the motor system is then unavailable to simulate the observed actions. Our results suggest that this relationship between action simulation and motor system preoccupation is a continuous one, such that the more available the motor system is, the more likely action simulation is to occur.

A classic body of research has suggesting the physical effort influence the visual perception of distances (Proffitt et al., 2003; Witt et al., 2011), object size (Witt et al., 2011) and hill slants (Bhalla & Proffitt, 1999; Proffitt, 2006). Proffitt and colleagues (2003) examined the influence of wearing a heavy backpack while making distance judgments of small cones various distances away from the observer. Half of the participants wore the heavy backpack while making the distance judgments while the other half of participants did not wear a backpack. Participants wearing the heavy backpack during the distance judgments overall reported the cones as farther away than participants not wearing backpacks. The authors suggest that this effect may be the result of anticipated effort need to reach each of the cones. Wearing a heavy backpack would magnify the amount of effort needed to walk to the cones, as opposed to not wearing a backpack, therefore, the cones appear farther away. Conversely, objects are reported as closer if the amount of physical effort needed to reach for the objects is reduced (Witt, 2011). The results from Experiment 3 would extend upon this research to suggest that physical effort used during action observation influences one's ability to correctly predict action outcomes. However, an alternative explanation for the relationship between physical effort and changes in visual sensitivity may be that participants are running multiple motor simulations (Vesper, van der Wel, Knoblich, & Sebanz, 2013), not that a single motor simulation is being disrupted. This possibility will be further discussed in the general discussion for Experiments 3 and 4.

Limitations. One uncontrolled factor in Experiment 3 was the amount of force participants used to pedal the mini bike. The results of Experiment 3 suggest that the amount of physical effort used to preoccupy the motor system during the observation phase may be an important influence on subsequent action prediction. It may be the case that we found no differences in visual sensitivity amongst our experimental groups because we did not account for individual physical effort. Future work should thoroughly manipulate the amount of force needed to pedal the mini bike and examine changes in visual sensitivity to predicting action outcomes.

Chapter 5: Investigating Improvements in Action Prediction with Visual Manipulations during Motor Tasks

5.1 Experiment 4: Action prediction of observed dart throwing: Visual manipulations

5.1.1 Hypothesis and theoretical motivation.

The goal of Experiment 4 was to establish if accuracy in action prediction is a function of visual and motor system interactions by varying the type of visual feedback participants receive during a motor task. The common coding theory suggests that visual representations and motor representations of actions overlap (Prinz, 1997). As such, several research studies have demonstrated that nonvisual motor training alone can lead to enhancements in visual sensitivity (Hecht et al., 2001; Beets et al., 2010; Casile & Giese, 2006; Brown et al., 2007). However, it is currently unclear how the addition of visual feedback of the observer's own limbs influences visual sensitivity. If the visual and motor representations of action share common codes, then changes in visual sensitivity could be magnified with the addition of visual feedback during motor training. Visual feedback of a limb in order to learn a novel motor skill appears to facilitate the learning process (Carroll & Bandura, 1982; Carroll & Bandura, 1985). In these studies, participants were instructed to make a series of arm movements with a paddle outside the visual field by wearing goggles to prevent vision of the arm. When participants were able to monitor their arm movements with concurrent visual feedback (via a video feed), learning the complex movements was superior to those participants without concurrent visual feedback. Therefore, although nonvisual motor training alone is sufficient to produce changes in visual sensitivity, it may be the case that the addition of visual feedback from the limbs may enhance motor learning and as a result visual sensitivity.

Participants in Experiment 4 performed the same action prediction task used in Experiment 3 before and after a visual or nonvisual motor task. Participants in the nonvisual motor training condition physically performed dart throwing without vision of their throwing arm. In this "invisible arm" condition, participants could feel their arm during the motor task but could not see their arm during performance. Similar to previous studies establishing that nonvisual motor training results in enhanced visual sensitivity (Hecht et al., 2001; Beets et al., 2010; Casile & Giese, 2006; Brown et al., 2007), participants in the "invisible arm" condition were expected display improvements in the action prediction task from before to after nonvisual motor training. Participants in the visual motor training conditions either physically performed dart throwing or basketball with full vision of their throwing arm. In the "visible arm" dart throwing condition, participants could see and feel their arm during the motor task. In accordance to the common coding theory (Prinz, 1997), the addition of visual feedback of the throwing arm should further enhance improvements in visual sensitivity to the action prediction task. Therefore, participants in the "visible arm" condition should also demonstrate improvements in predicting action outcomes from before to after visual motor training, however, the magnitude of improvement should be above and beyond that of participants in the "invisible arm" condition. Finally, in the basketball control condition, participants could see and feel their arm during the physical performance of the unrelated motor task. Although in this condition participants share similarities in feedback with participants in the "visible arm" condition, the basketball task is unrelated to dart throwing. Participants in this condition should show little to no improvement in the action prediction task from before to after visual motor training as the motor task performed is uninformative to dart throwing. The results of Experiment 4 aim to better understand the mechanisms underlying perception-action coupling, and specifically the common coding theory.

5.1.2 Methods.

Participants. 81 Rutgers University – Newark undergraduate students (mean age = 21.05 years, 45 females and 36 males) were recruited to participate for partial course credit. All of the participants were right handed with normal or corrected to normal vision and no dart throwing experience. Of the initial 81 participants, 21 were eliminated from data analysis for performing below chance (50% accuracy) in the pre-action prediction task, below chance (50% accuracy) in the post-action prediction task or at chance in both the pre- and post-action prediction tasks. The resultant group of participants used in the final statistical analyses included 60 participants (mean age = 20.83 years, 29 females and 31 males). These 60 participants were randomly assigned to one of the three experimental conditions.

Materials. Experiment 4 consisted of three parts: the pre-action prediction task, a motor task with a visual manipulation, and the post-action prediction task. The pre- and post-action prediction task is the same task from Experiment 3 and participants' responses were once again captured using E-prime 2.0 software (Psychological Software Tools, Inc.) on the same iBuyPower computer and Spectre monitor used in Experiment 3.

After the pre-action prediction task, participants performed a motor task in one of three different conditions. The motor tasks employed in Experiment 4 were either a dart throwing task or a Nerf basketball task. The darts, which were the same as the darts used in Experiments 1 and 2, were Harrow brand darts weighing 24g. Participants in dart throwing motor tasks were asked to throw the darts as accurately as possible at the yellow goal area of the target (8cm in diameter, see Figure 1). Participants in the basketball motor task shot palm-sized, malleable Nerf basketballs at a hoop (24.5cm in diameter). The visual manipulation of the motor task removed participants' vision of the throwing arm through use of a tunnel (Figure 33). The tunnel was constructed to be large enough for a participant to place their face in the opening. The tunnel was 15 inches long and made of black foam boards. To adjust the tunnel to the heights of different participants, the tunnel was attached to a microphone stand.

Participants completed the Action Experience Survey at the end of the experiment. This survey was created to examine individual differences amongst participants in their self-reported experience throughout the experiment. The survey is 22 questions long and asked participants to report their confidence level of judgments to the pre- and post-action prediction task. Questions also inquired about the subjective experience of performing the motor task. These questions aimed to determine how aware participants were of feeling or seeing (if applicable) their arm while executing the action. Finally, an open-ended question was included at the end to determine what visual information participants were using to respond in the pre- and post-action prediction task. A copy of the Action Experience Survey can be found in Appendix B.

Figure 33. The tunnel used in the dart throwing condition, blocking vision of the throwing arm. The tunnel is 15 inches long and is large enough for participants to place their face in the opening. The tunnel was attached to a microphone stand to adjust for participants of various heights.

Design. Participants completed each of the three experimental phases in the following order: the pre-action prediction task, the motor task with visual manipulation, and the post-action prediction task (Figure 34). Assignment to one of the three possible experimental conditions was randomized in this between-subjects design.

Procedure. First, all of the participants performed the same 2AFC pre-action prediction task described in Experiment 3, viewed on the same computer screen in Experiment 3 from approximately 61cm away. The goal of the action prediction task was for participants to determine whether each partial dart throw would “hit” or “miss” the yellow goal area of the target.

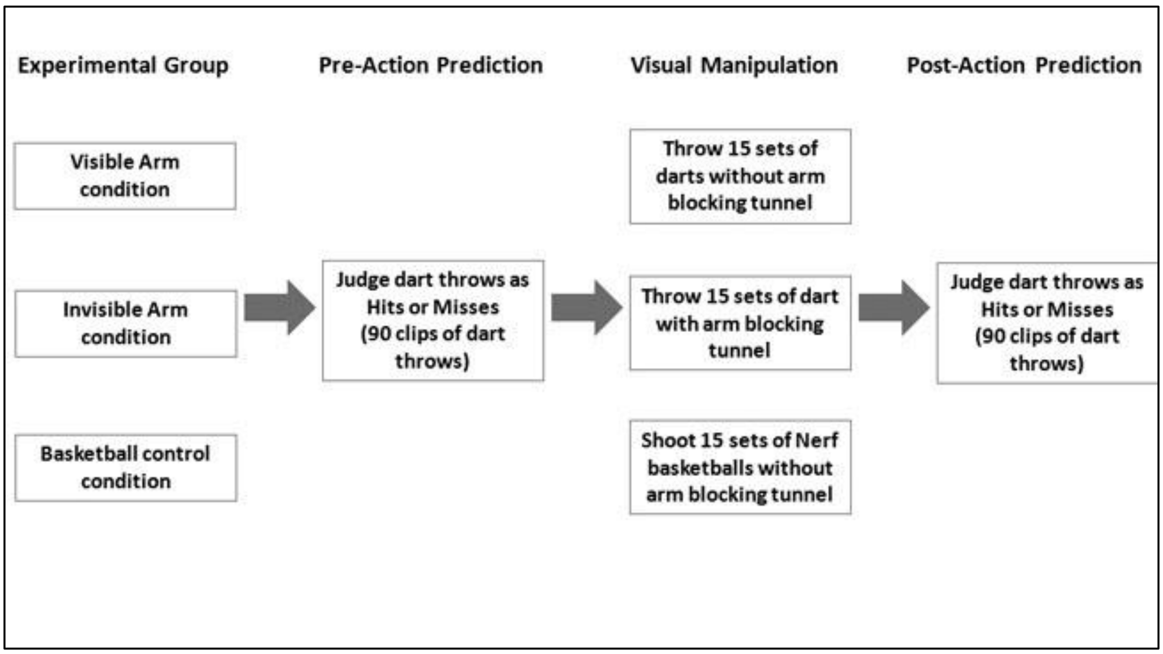
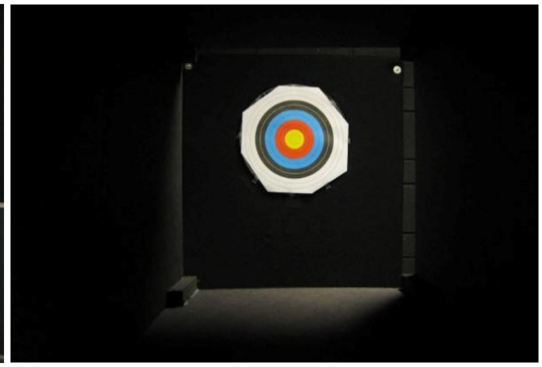


Figure 34. Experiment 4 design. Participants were randomly assigned to one of three different visual manipulations while concurrently performing a motor task. All of the participants completed the pre-action prediction task, followed by the motor task, and finally the post-action prediction task.

Following the pre-action prediction task the participants performed in one of the three motor tasks. Participants (1) threw darts as accurately as possible at the target with full vision of their throwing arm (visible arm condition), (2) threw darts as accurately as possible at the target with *no vision* of their throwing arm (invisible arm condition), or (3) shot Nerf basketballs at a hoop as accurately as possible with vision of their shooting arm (basketball control condition).



Figures 35 and 36. Photographs of the "invisible arm" dart throwing condition in Experiment 4. The tunnel was adjusted to each participant's individual height and comfort. Participants in this condition were instructed to place their face into the opening of the tunnel to block the vision of their throwing arm during the motor task (Figure 35, on left). Figure 36 (on the right) depicts the participants' point of view when looking through the tunnel.

Participants in the visible arm dart throwing condition threw 15 sets of darts (a set contained three individual darts) at the target with the goal of throwing as many darts as possible into the yellow goal area. These participants had both kinesthetic feedback from the throwing motion (the feeling of throwing the dart) as well as visual feedback from the throwing motion (seeing the dart throw). Participants in the invisible arm dart throwing condition were instructed to throw 15 sets of darts at the yellow goal area of the target as accurately as possible. However, before starting the motor task, the tunnel was adjusted to the height and comfort of each participant (Figure 35). Once the tunnel was adjusted appropriately, the experimenter asked participants if they could see their dart throwing arm to ensure the visual manipulation worked. After setting up the tunnel, participants in this condition threw 15 sets of darts as accurately as possible at the target. Using the tunnel allowed participants kinesthetic feedback of the throwing motion but not visual feedback of the throwing arm (see Figure 36 for the participants' point of view in this experimental condition). Finally, participants in the basketball control condition shot 15 sets of balls at a hoop as accurately as possible (Figure 37). One set of balls included three individual balls, to equate the motor task with the dart throwing conditions. In this condition, participants had both kinesthetic and visual feedback of the shooting arm, yet the task is unrelated to dart throwing. All of the participants physically performed the motor tasks while standing 7’9” away from the target/hoop.

After the motor task manipulation, all of the participants again completed the post-action prediction task. The presentation order of the individual dart throw stimuli were randomized so that there were no potential sequence effects. Finally, all of the participants filled out the Action Experience Survey (see Appendix B). The entire experiment lasted approximately 30 minutes.

Figure 37. A photograph of the basketball motor task control condition in Experiment 4. Participants threw balls as accurately as possible with the goal of getting as many balls as possible into the hoop.

Analyzing motor performance. In Experiments 1 and 2, dart throwing motor performance was calculated as a continuous variable. Participants aimed and threw darts at a target, leaving a way to physically measure distances of different dart throws. While the data in the visible and invisible arm dart throwing conditions for Experiment 4 could be quantified in the same way as in Experiments 1 and 2, there was no way to compute the basketball performance in a similar manner. In the basketball control condition for this current experiment, the only evidence of motor performance was the video footage of each participant. From this footage, motor performance for the basketball condition could be categorized in four ways. First, the ball goes in the hoop extremely accurately, or in other words, hits nothing but net. Second, the ball goes in the hoop less accurately, hitting the rim before going into the hoop. Third, the ball misses the hoop but hit the rim before missing. Fourth, the ball misses the hoop extremely inaccurately, or in other words, is an airball. These four categories were coded from 1 (nothing but net) to 4 (airball) to give some sense of magnitude to accurate basketball motor performance.

To equate the coding system employed for the basketball motor performance with dart throwing motor performance, the motor outcomes in visible and invisible arm conditions were also coded into four categories based on where individual darts landed on the target. Each individual dart throw was coded from the most accurate (1 = darts landed in yellow rings), somewhat accurate (2 = darts landed in red or blue rings), somewhat inaccurate (3 = darts landed in black or white rings), to least accurate dart throws (4 = darts missed the target). Figure 38 shows the coding system utilized in the visible and invisible arm conditions. Similar to the coding system used for the basketball motor performance, these four categories give some sense of magnitude to accurate dart throwing motor performance and allow for comparison across different motor tasks.

Figure 38. A depiction of the four category coding system for accurate dart throwing performance in the visible and invisible arm conditions in Experiment 4. The codes range from the most accurate performance ("1", yellow rings) to the most inaccurate performance ("4", misses).

5.1.3 Results.

The results for average d' score, average percentage correct for video clips that would have resulted in hits, high misses and low misses in the pre- and post-action prediction tasks sorted by experimental group can be seen in Table 33.

Condition	d' Before	d' After	% Correct Hits Before	% Correct Hits After	% Correct High Miss Before	% Correct High Miss After	% Correct Low Miss Before	% Correct Low Miss After
Visible Arm	**1.137** (SE=.12)	**2.189** (SE=.38)	**69%** (SE=.03)	**83%** (SE=.03)	**64%** (SE=.04)	**58%** (SE=.05)	**77%** (SE=.03)	**79%** (SE=.04)
Invisible Arm	**1.259** (SE=.17)	**1.883** (SE=.21)	**70%** (SE=.03)	**84%** (SE=.02)	**65%** (SE=.05)	**66%** (SE=.05)	**79%** (SE=.05)	**79%** (SE=.05)
Basketball	**1.388** (SE=.12)	**1.786** (SE=.15)	**70%** (SE=.03)	**73%** (SE=.03)	**76%** (SE=.04)	**76%** (SE=.05)	**79%** (SE=.05)	**87%** (SE=.03)

Table 33. The average d' scores and percentage correct for video clips that would have resulted in hits, misses high and low by the three experimental conditions. The higher d' score observed, the greater visual sensitivity to the dart throwing clips. Percentage correct for clips resulting in hits, high or low misses are presented in percentages.

Pre-action prediction task. To determine whether the experimental groups were equivalent in terms of d' scores and percentage correct before the manipulation in the pre-action prediction task, several one-way ANOVAs were conducted. The average d' scores in the pre-action prediction task did not significantly differ across the four experimental groups (F (2, 57) = .420, p = .659, n_p^2 = .015). Additionally, the participants in the different experimental groups did not significantly differ in their correct percentages in the pre-action prediction task clips that would result in hits (F (2, 57) = 1.472, p = .238, n_p^2 = .049), high misses (F (2, 57) = .334, p = .717, n_p^2 = .012), and low misses (F (2, 57) = .722, p = .490, n_p^2 = .025). The results of these analyses suggest that the experimental groups did not differ before the manipulation during the motor task.

Performance before and after the observation phase. Performance in the pre- and post-action prediction tasks were examined with a series of mixed model ANOVAs in which the between-subjects variable is the motor task condition and the within-subjects variables are d' scores and percent correct for clips resulting in hits, high and low misses in the pre- and post-action prediction tasks. The results of the mixed model ANOVA for d' scores can be found in Table 34.

	Main Effect of Time (before/after)	**Main Effect of Group (motor task condition)**	**Interaction of Time * Group**
F-test for average d'	F(1, 57) = 10.265, ***p* = .002**, n_p^2 = .153	F(2, 57) = .072, p = .930, n_p^2 = .003	F(2, 57) = .838, p = .438, n_p^2 = .029

Table 34. Results from the 3 (experimental motor tasks) x 2 (before and after performance) mixed model ANOVA for d' scores. The between subjects variable is the motor task condition and the within subjects variable is the average d' scores before and after the manipulation.

For average d' scores, the mixed model ANOVA revealed a significant main effect of time (F (1, 57) = 10.265, p = .002, n_p^2 = .153), such that overall performance, as indicated by higher d' scores, was better in the post-action prediction task as compared to the pre-action prediction task. As can be seen in Figure 39, all of the participants in each of the experimental groups improved from the pre- to post-action prediction task in terms of d' scores. There were no other significant main effects or interactions (*p* > .05).

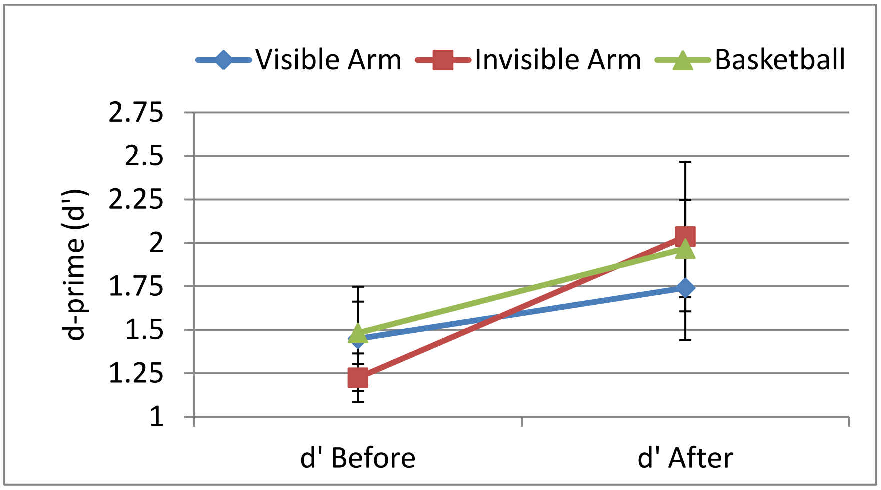


Figure 39. The average d' scores before (pre-action prediction task) and after (post-action prediction task) by experimental condition.

To examine the changes in d' from before to after the motor task, a difference score was created by subtracting the d' scores in the post-action prediction task from the d' scores in the pre-action prediction task. The resultant variable (change in d') reveals improvement in d' scores with a positive number and a decline in d' scores with a negative number. Figure 40 shows the amount of change in d' over the course of the experiment by experimental group. Again, this figure demonstrates that all of the experimental groups improved in visual sensitivity from the pre- to post-action prediction tasks although there were no differences amongst the groups ($F(2, 57) = .838$, $p = .438$). Surprisingly, participants in the invisible arm dart throwing condition showed the greatest improvement, as illustrated by the largest positive change in d' scores. Participants in the basketball condition demonstrated improvement in d' scores overall, which also was unexpected.

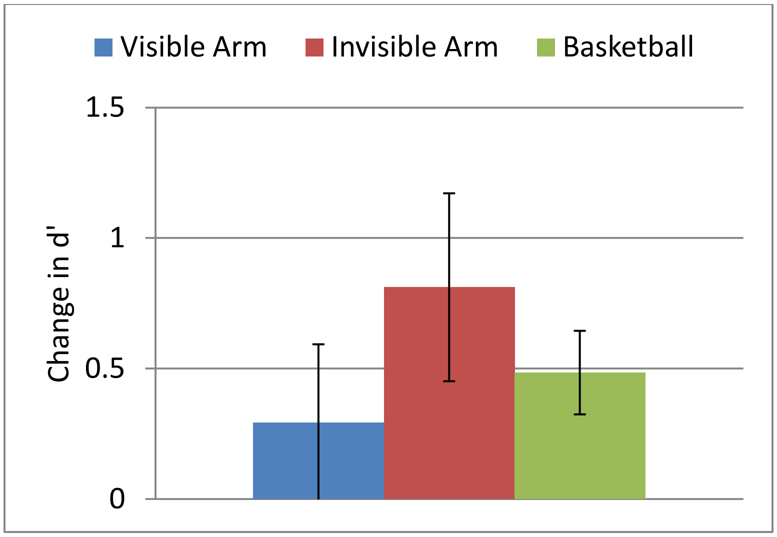


Figure 40. The change in average d' scores before (pre-action prediction task) and after (post-action prediction task) by experimental condition. Positive scores indicate improvement from the pre- to post-action prediction tasks, while negative scores indicate decline in performance.

The results from the mixed model ANOVA for the average percentage correct for clips resulting in hits can be found in Table 35. For the percent correct of "hit" clips, the mixed model ANOVA showed a marginally significant main effect of time ($F(1, 57) = 3.556$, $p = .064$, $n_p^2 = .059$) such that participants were more correct after the manipulation in the post-action prediction task than before. Figure 41 shows the average percent correct for video clips resulting in hits by each experimental group both before (pre-action prediction task) and after (post-action prediction task) the manipulation. There were no other significant main effects or interactions ($p > .05$).

	Main Effect of Time (before/after)	**Main Effect of Group (motor task condition)**	**Interaction of Time * Group**
F-test % Correct for Hits	$F(1, 57) = 3.556$, $\boldsymbol{p = .064}$, $n_p^2 = .153$	$F(2, 57) = 2.214$, $p = .119$, $n_p^2 = .072$	$F(2, 57) = .119$, $p = .827$, $n_p^2 = .007$

Table 35. Results from the 3 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percentage correct for "hit" clips. The between subjects variable is the motor task performed and the within subjects variable is the average percent correct before and after the manipulation.

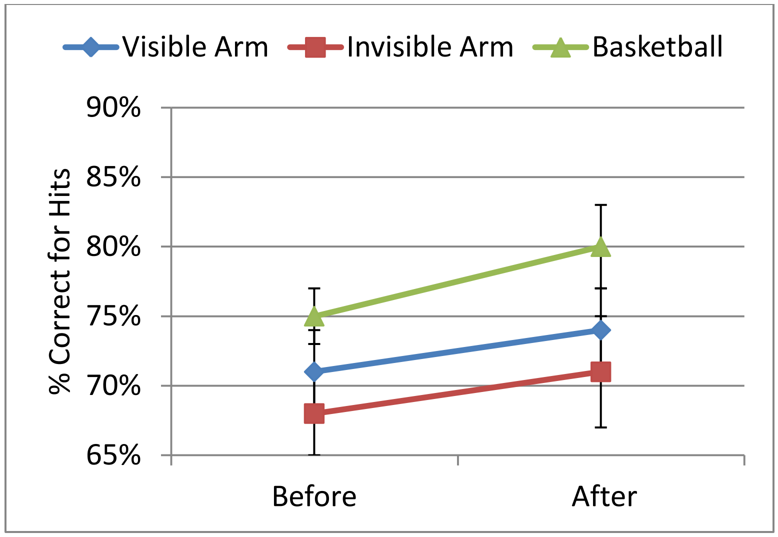


Figure 41. The average correctness for "hit" video clips before (pre-action prediction task) and after (post-action prediction task) by experimental condition.

The results for the mixed model ANOVA on the average percentage correct for video clips resulting in misses above the yellow goal area (high misses) can be found in Table 36. The results for the main effect of time, main effect of group, and the interaction of time and experimental group did not reach significance (p >.05).

	Main Effect of Time (before/after)	**Main Effect of Group (motor task condition)**	**Interaction of Time * Group**
F-test % Correct for High Misses	$F(1, 57) = .464$, $p = .498$, $\eta_p^2 = .008$	$F(2, 57) = .132$, $p = .877$, $\eta_p^2 = .005$	$F(2, 57) = .380$, $p = .686$, $\eta_p^2 = .013$

Table 36. Results from the 3 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percentage correct for video clips resulting in misses above the yellow goal area. The between subjects variable is the motor task performed and the within subjects variable is the average percent correct before and after the manipulation.

Lastly, the results for the mixed model ANOVA for the average percentage correct of video clips resulting in misses below the yellow goal area (low misses) before (pre-action prediction task) and after (post-action prediction task) the motor task by group revealed a significant main effect of time (F (1, 57) = 11.223, p = .001, n_p^2 = .165) (see Table 37). As can be seen in Figure 42, overall participants showed improved performance for video clips resulting in misses below the yellow goal area from the pre- to post-action prediction tasks. The main effect of group and the interaction between time and experimental group did not reach significance (p > .05).

	Main Effect of Time (before/after)	Main Effect of Group (motor task condition)	Interaction of Time * Group
F-test % Correct for Low Misses	F(1, 57) = 11.223, **p = .001**, n_p^2 = .165	F(2, 57) = .548, p = .581, n_p^2 = .019	F(2, 57) = .625, p = .539, n_p^2 = .021

Table 37. Results from the 3 (experimental condition) x 2 (before and after performance) mixed model ANOVA for percentage correct of video clips resulting in misses below the yellow goal area. The between subjects variable is the motor task performed and the within subjects variable is the average percent correct before and after the manipulation.

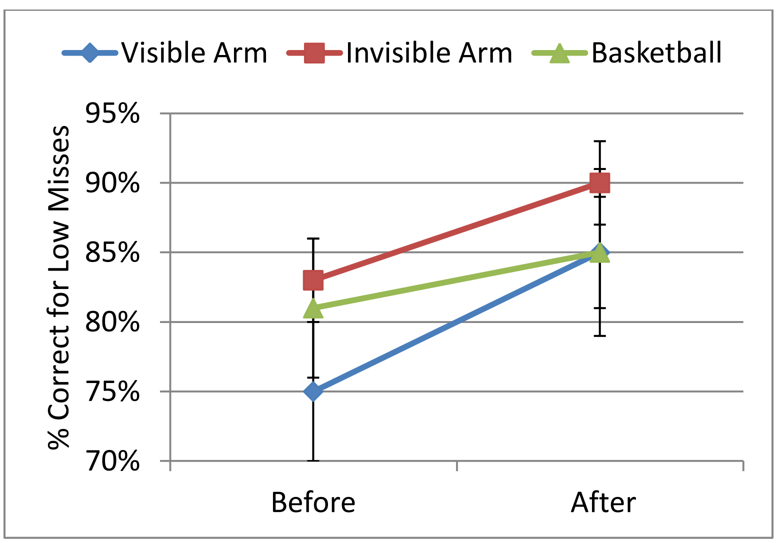


Figure 42. The average percentage correct for "low miss video clips before (pre-action prediction task) and after (post-action prediction task) by experimental condition.

Motor performance and changes in visual sensitivity to action prediction. In the different motor tasks between the pre- and post-action prediction tasks, participants' performance was categorically coded such the dart throwing conditions (visible and invisible arm) and the basketball condition could be comparable. A numerical place holder was coded for each individual dart throw/basketball shot. In total, there were data points for each of the 15 sets of throws/shots (45 individual throws/shots). This data was combined into phases such that motor performance over time could be analyzed. Table 38 describes how the data was combined into phases.

Phase	**Description**
Phase 1	Average of all categorical data from dart or basketball Sets 1 - 3
Phase 2	Average of all categorical data from dart or basketball Sets 4 - 6
Phase 3	Average of all categorical data from dart or basketball Sets 7 - 9
Phase 4	Average of all categorical data from dart or basketball Sets 10 - 12
Phase 5	Average of all categorical data from dart or basketball Sets 13 - 15

Table 38. Description of phase data by sets for Experiment 4. Each phase consists of three set of darts/basketballs (or nine individual throws/shots). Phase data were plotted for average motor performance accuracy over the course of the motor task by experimental condition.

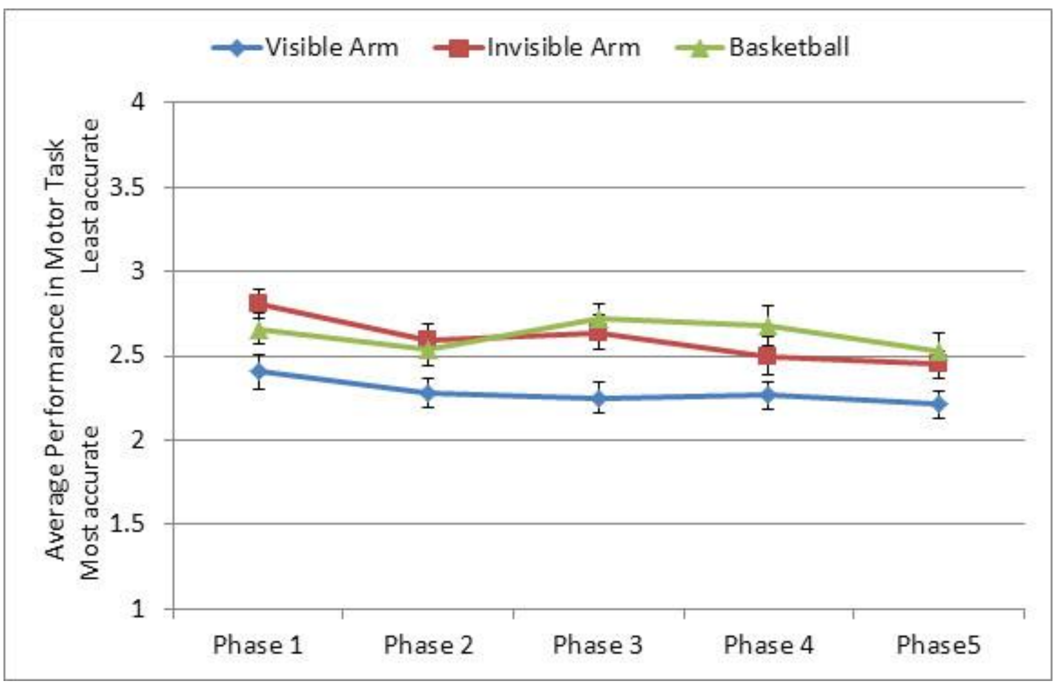


Figure 43. Average motor performance by each experimental group over the course of the motor task.

Figure 43 above graphically represents the average motor performance by each experimental group over the five phases during the motor task based on the categorical data described above. Higher average scores represent the *least* accurate motor performance while lower average scores represent the *most* accuracy performance.

To calculate changes in motor performance over the course of the motor task, the average performance scores from Phase 1 were subtracted from the average performance scores in Phase 5 (Phase 5 – Phase 1), Phase 4 (Phase 4 – Phase 1), Phase 3 (Phase 3 – 1) and Phase 2 (Phase 2 – Phase 1) for each experimental group. A negative difference score represents an improvement in motor performance over the motor task. In other words, negative scores indicate that motor performance was more accurate over time. A positive score represents a decline in performance over the motor task, or that motor performance becomes more inaccurate over time. The differences scores are presented in Table 39. As can be seen in Table 39, participants in the visible and invisible arm dart throwing conditions became more accurate over the course of the motor task in each of the difference score calculations. Participants in the basketball condition showed improvement when the difference scores were calculated in relation to Phases 2 and 5. However, when the difference scores were calculated in relation to Phases 3 and 4, the basketball condition showed no improvement in motor performance. In all cases, participants in the invisible arm condition showed the greatest improvement as compared to the other experiment conditions.

	Visible Arm	**Invisible Arm**	**Basketball**
Phase 5 – 1 Average	-.1944 (SE = .08)	-.3556 (SE = .09)	-.1345 (SE = .12)
Phase 4 – 1 Average	-.1389 (SE = .07)	-.3056 (SE = .07)	-.0058 (SE = .10)
Phase 3 – 1 Average	-.1566 (SE = .06)	-.1667 (SE = .08)	.0702 (SE = .09)
Phase 2 – 1 Average	-.1278 (SE = .10)	-.2167 (SE = .09)	-.1287 (SE = .09)

Table 39. Difference scores calculated for each experimental group to quantify change in motor performance during the motor task. Difference scores were calculated by subtracting the average performance scores in Phase 1 from Phases 2 -5. Negative numbers indicate improvement in accurate performance while positive numbers represent a decline in performance.

To determine if the participants in the motor conditions showed differences in the rates of improvement during the motor task, one-way ANOVAs were conducted on each of the difference scores. The experimental groups demonstrated no differences in the rates of change in motor performance from Phase 1 to Phase 5 (F (2, 56) = 1.336, p = .271, n_p^2 = .046) or from Phase 1 to Phase 2 (F (2, 56) = .292, p = .748, n_p^2 = .010). When comparing the groups on changes in motor performance from Phase 1 to Phase 4, there was a significant difference between the groups (F (2, 56) = 3.327, p = .043, n_p^2 = .106). Specifically, the participants in the invisible arm condition improved more in average accuracy than participants in the basketball control condition (F (2, 56) = 3.327, p = .034). Moreover, when examining changes in motor performance from Phase 1 to Phase 3, there was a marginally significant difference between the experimental groups (F (2, 56) = 2.887, p = .064, n_p^2 = .093). Again, this marginally significant difference was driven by participants in the invisible arm condition performing more accurately over time as compared to participants in the basketball condition.

Is change in motor performance accuracy during the motor task related to change in visual sensitivity during the action prediction task? A series of Pearson's correlations were conducted to determine if the difference scores (representing change in motor performance) were related to change in d' scores from the pre- to post-action prediction tasks for each of the experimental groups. Surprisingly, none of the correlations reached significance (p > .05) indicating that motor performance during the motor tasks was not significantly related to changes in visual sensitivity in predicting action outcomes.

Self-report measures and changes in visual sensitivity to action prediction. Following the conclusion of the experiment, all of the participants filled out the Action Experience Survey (see Appendix B for a full version). These questions were designed to ask participants about their subjective experience throughout the experiment. Questions #1 and #22 asked participants to rate how accurately they performed in the pre- and post-action prediction tasks on a scale from 1 (not at all accurate) to 5 (extremely accurate). There was an overall positive correlation between how accurately participants felt they performed in the pre-action prediction task and change in d' from the pre- to post action prediction tasks (r = .363, *p* = .004). This correlation was driven by participants in the visible arm dart throwing task (r = .459, *p* = .042) and participants in the invisible arm dart throwing task (r = .541, *p* = .014). In other words, as participants in both dart throwing conditions felt more confident in their performance during the pre-action prediction task, the greater changes in d' scores observed (see Figure 44).

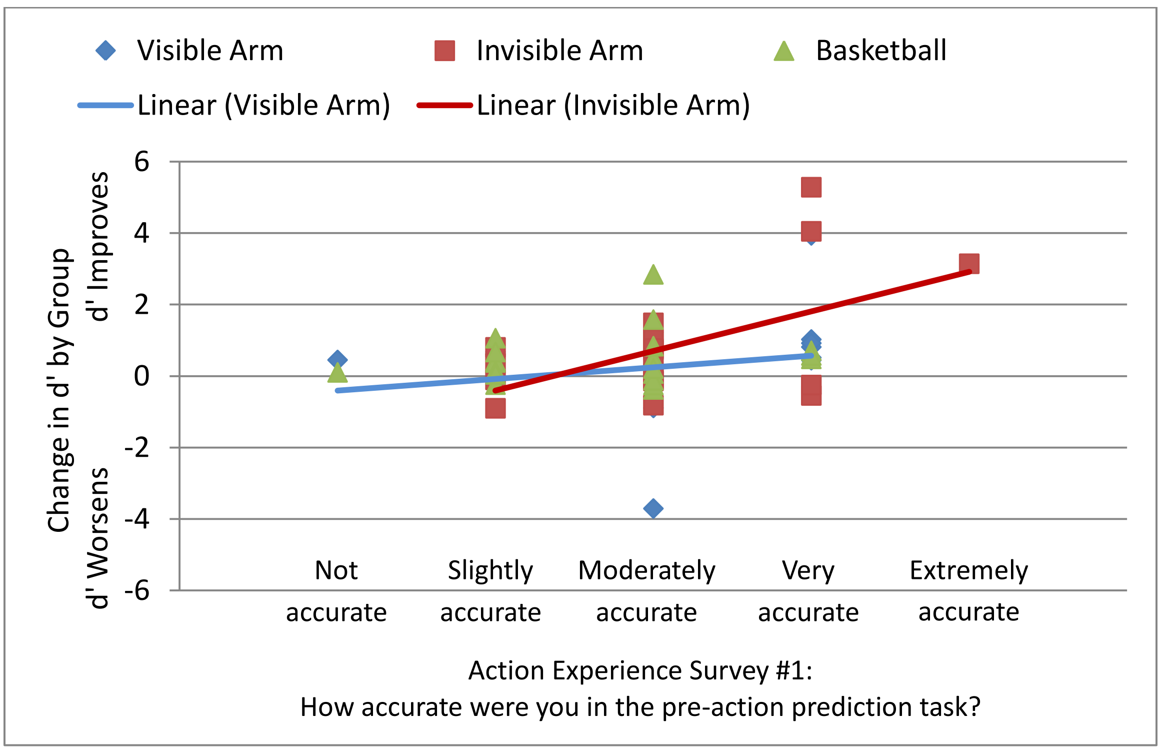


Figure 44. Correlation between the self-reported accuracy during the pre-action prediction task and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) the experimental manipulation by condition.

Questions #3 - #6 on the Action Experience Survey generally asked participants how important they believed feeling or seeing their throwing arm during the task was to overall physical performance. There were no overall correlations between these survey questions and changes in d' scores, however, when examining these correlations by experimental group one correlation was significant. For participants in the invisible arm condition, the more important they rated feeling their arm during the motor task, the greater change observed in d' scores (r = .501, *p* =.024, see Figure 45). Therefore, it appears that participants in the invisible arm condition relied more on kinesthetic feedback than other experimental groups.

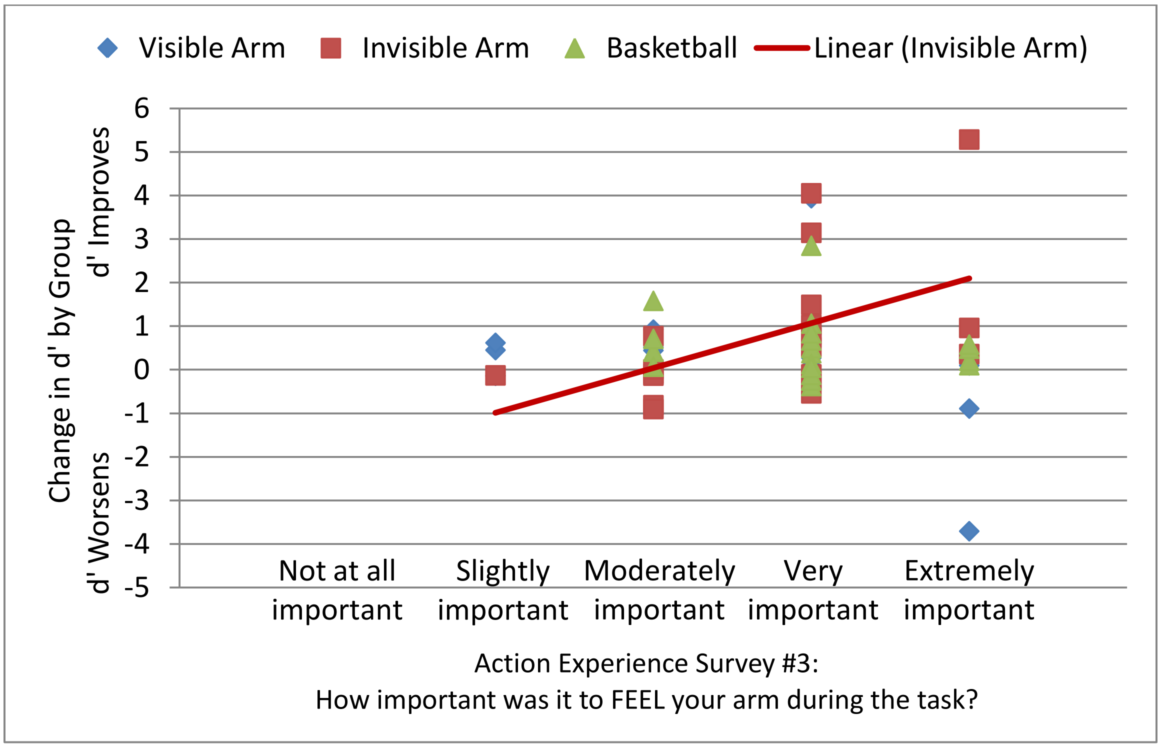


Figure 45. Correlation between the self-reported importance of feeling the arm during the motor task and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) the experimental manipulation by condition.

The next group of questions on the Action Experience Survey (questions #7 - #11) asked participants to report how aware they were of seeing (if applicable) or feeling their arm during the motor task. Again, there were no correlations overall, however, there were significant correlations when examining the experimental groups separately. There was a positive correlation between the change in d' scores from the pre- to post-action prediction tasks and how aware participants in the invisible arm condition were of feeling their throwing arm (r = .445, *p* =.013, see Figure 46). The more aware participants in the invisible arm condition were of their arm movement during the dart throwing task, the greater observed change in d' scores.

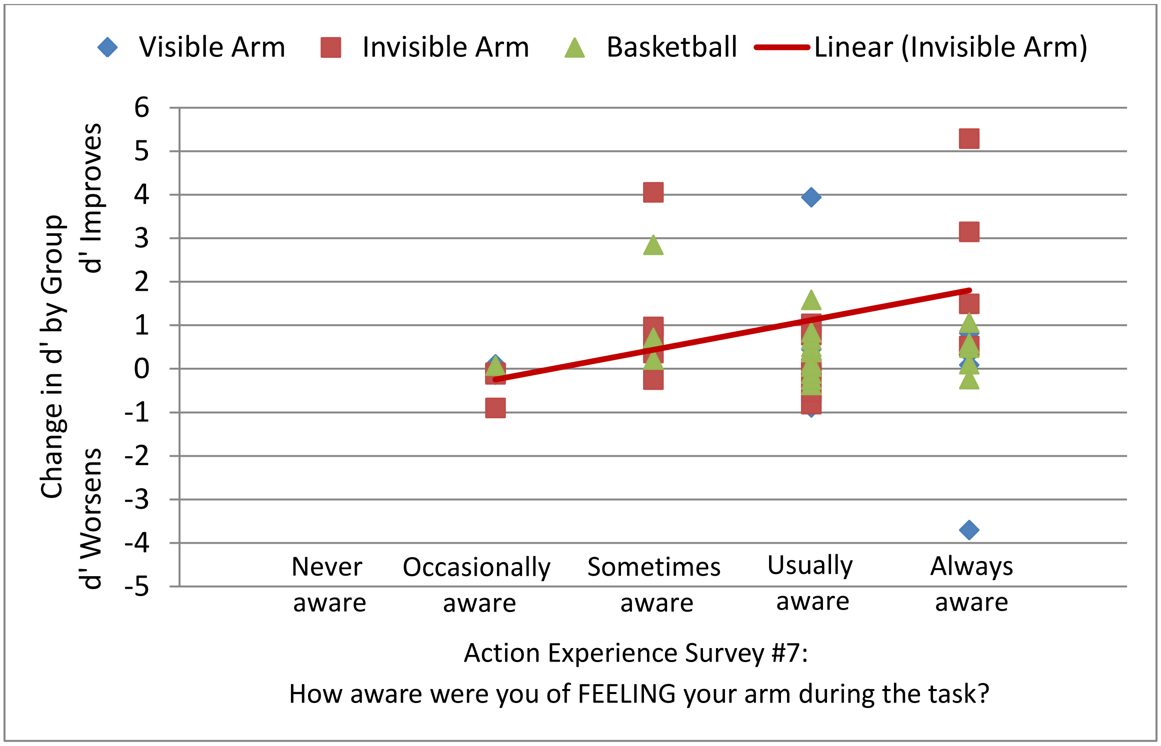


Figure 46. Correlation between the self-reported awareness of feeling arm during motor task and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) the experimental manipulation by condition.

Furthermore, for participants in the invisible arm condition, there was a positive correlation between changes in d' scores and awareness of hand placement on the dart (r = .454, *p* = .044, see Figure 47). Again, the more aware participants in this condition were of how they held the dart, the greater changes in d' from the pre- to post-action prediction tasks that were observed. This is line with the previous correlation further suggesting that participants in the invisible arm condition relied more on the kinesthetic feedback during the motor task than participants in the other conditions.

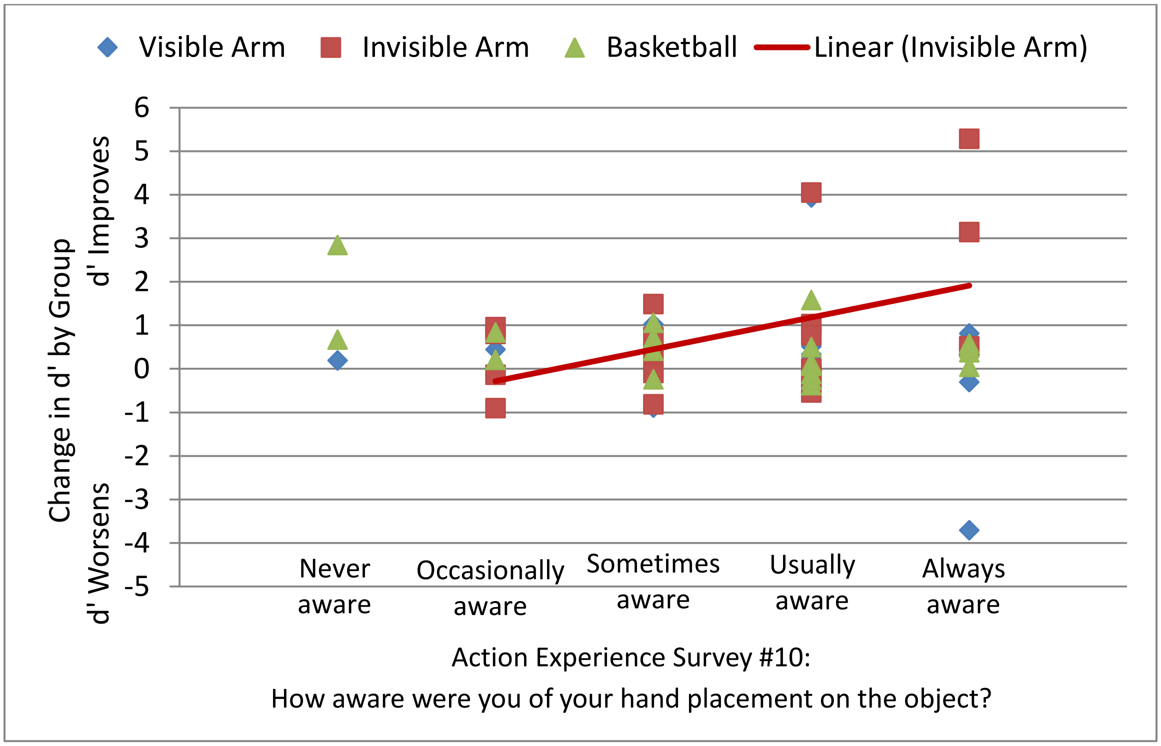


Figure 47. Correlation between the self-reported awareness of hand placement on the thrown object and change in d' scores from before (pre-action prediction task) to after (post-action prediction task) the experimental manipulation by condition.

The final group of questions (questions #12 - #20) asked participants whether they believed improvements in the motor task were a function of feeling or seeing their throwing arm, the object, or the action outcome. Overall, there was a positive correlation between change in d' scores and how helpful participants believed seeing the action outcome was to motor performance improvement (r = .321, *p* = .013). This correlation was driven by participants in the visible arm condition (r = .629, *p* = .003). In other words, the more participants in the visible arm condition thought seeing the action outcome was to improving at the motor task, the greater change in d' scores from the pre- to post-action prediction tasks. Thus, while participants in the invisible arm condition appear to rely on kinesthetic feedback more than participants in the other conditions, the participants in the visible arm condition appear to rely on the visual feedback of the action outcome.

Finally, the Action Experience Survey included an open-ended question asking participants what led them to respond “hit” or “miss” following the action prediction video clips. Specifically, this question reads, “What about the video informed you whether the dart throw would hit or miss the yellow area?”. Based on the answers from the participants overall, one of three things informed their decisions. Participants used the dart’s location on the screen or trajectory, the model’s arm or wrist movements, or a combination of the both the dart and model’s arm movement. Participant responses revealed that 19 participants used the dart’s movements alone, 30 participants used the model’s arm movement alone, and 10 participants used a combination of both the dart and model’s arm movement. Similar to Experiment 3, it is important to rule out that participants did not simply use information specific to the dart trajectory to respond (although they do not see the outcome of the dart throw) and improve at the action prediction task above and beyond that of participants using the model’s arm movement or a combination of visual information. Using the participant responses to this question as the grouping variable, a one-way ANOVA was conducted examined differences in d’ scores from the pre- to post-action prediction task. The results showed no differences amongst the type of visual information participants self-reportedly used to respond during the action prediction tasks and changes in d’ scores (F (2, 56) = .534, p = .589).

5.1.4 Discussion.

Experiment 4 examined the influence of visual feedback from the throwing arm during a motor task on subsequent visual sensitivity in the action prediction task as compared to nonvisual motor training. Based on the results of previous studies demonstrating the nonvisual motor training can inform subsequent visual discrimination task performance (Hecht et al., 2001; Beets et al., 2010; Casile & Giese, 2006; Brown et al., 2007), participants in the "invisible arm" condition were expected to show an improvement in visual sensitivity from the pre- to post-action prediction tasks. The common coding theory of perception and action (Prinz, 1997) states that visual representations and motor representations of action overlap, allowing for improved visual discrimination following nonvisual motor training. In Experiment 4, the purpose of the "visible arm" condition was to determine if visual feedback while performing the dart throwing task would magnify changes in visual discrimination. Thus, participants in the "visible arm" condition were hypothesized to show improvement from the pre- to post-action prediction tasks above and beyond that of the "invisible arm" group as these participants had both kinesthetic and visual feedback during the motor task. Finally, little to no change was expected in performance from the pre- to post-action prediction tasks in the basketball control group as the physical performance of basketball is unrelated to dart throwing. In terms of common coding, the visual and motor representations produced by performing the basketball task are not the same visual and motor representations produced from dart throwing, therefore, the physical performance of basketball should be uninformative to the visual discrimination of observed dart throwing.

The results of Experiment 4 revealed that the experimental groups did not statistically differ in terms of change in visual sensitivity (d') from the pre- to post-action prediction task as a function of the physically performed motor task. Furthermore, the groups were more correct for video clips resulting in hits or low misses after the manipulation. Similar to Experiment 3, participants in Experiment 4 did not show improvement for video clips resulting in high misses again implying that these video clips were more difficult to discriminate. Overall, these results suggest that physical performance of the different motor tasks all informed the visual discrimination of accurate or inaccurate dart throws. However, there was no relationship between motor performance and changes in visual sensitivity to dart throwing outcomes. In other words, changes in visual sensitivity were not reliant on improving accuracy throughout the motor task.

The initial hypotheses were partially supported, in spite of some of the unanticipated results. Previous research has shown that nonvisual motor training can lead to enhancements in visual sensitivity (Hecht et al., 2001; Beets et al., 2010; Casile & Giese, 2006; Brown et al., 2007). The results for participants in the "invisible arm" condition are in line with this estimation, as even without vision of the throwing arm, this group was able to better discriminate observed dart throws after the motor task. Furthermore, enhanced visual sensitivity to predicting dart throwing outcomes following nonvisual motor training supports the common coding theory (Prinz, 1997). Surprisingly, although the difference was not statistically significant, participants in the "invisible arm" condition displayed the greatest improvement in visual sensitivity to predicting dart throwing outcomes as compared to participants in the other experimental conditions. From the self-reported data it may also be the case that these participants were more aware of their body and throwing movement during the task. Following the post-action prediction task, participants filled out the Action Experience Survey. Participants in the "invisible arm" condition exhibited relationships between the kinesthetic feedback of the throwing arm during the dart throwing task and changes in visual sensitivity from the pre- to post-action prediction tasks. Specifically, the more importance placed on feeling the arm, the more aware of feeling the throwing arm, and the more aware of hand placement on the dart participants reported, the greater change observed in visual sensitivity. This could insinuate that the more participants used kinesthetic feedback while performing the motor task, the more aware participants subsequently were of crucial elements in the partial dart throws of the post-action prediction task.

Against initial predictions, the participants in the "visible arm" condition showed the least amount of change in visual sensitivity from the pre- to post-action prediction tasks. Carroll and Bandura (1982; 1985) found that motor learning was promoted by visually monitoring one's limb movements. As such, participants in the "visible arm" condition were expected outperformed participants in the "invisible arm" condition in terms of the magnitude of change in visual discrimination. This hypothesis was not supported in Experiment 4. The survey results could suggest that participants in the "visible arm" condition were not as aware of their body or throwing movement which in turn could possibly explain the smaller amount of improvement in the action prediction tasks. Unlike participants in the "invisible arm" condition, participants in the "visible arm" condition answered survey questions in a way that did not present a relationship between kinesthetic feedback during the dart throwing task and changes in visual sensitivity. For participants in this condition, the more helpful seeing the action outcome, or where the dart landed, was rated, the greater change in visual sensitivity from the pre- to post-action prediction tasks.

Experiment 4 also suggests that changes in visual sensitivity to predicting dart throwing outcomes do not appear to be reliant on physically performing a dart throwing task. Participants in the basketball condition showed similar levels of improvement in the action prediction task as the other groups. These results were quite unexpected. It is very interesting that even when participants performed an unrelated motor task to dart throwing, there were still improvements in visual sensitivity to different dart throws. It important to note that in the pre- and post-action prediction tasks, participants never received feedback on their performance. Therefore, participants never knew whether they correctly or incorrectly judged individual dart throws. In other words, changes in visual sensitivity cannot simply be explained through visual exposure to the dart throwing video clips. Improved visual sensitivity to dart throwing outcomes for participants who physically performed basketball could suggest that dart throwing and basketball share similarities on an athletic level. For example, both the dart throwing and basketball tasks are nonballistic aiming motor tasks. In other words, participants have control of the movement from the initiation of the movement to the time of release of the dart or ball (Vesper et al., 2013).   In the general discussion, similarities between the basketball and dart throwing tasks and how that relates to changes in visual discrimination will be discussed.

2.3 General Discussion of Experiments 3 and 4

Experiments 3 and 4 attempted to systematically investigate the roles of the visual and motor systems as it relates to action simulation and perception-action coupling at large. Experiment 3 found that when participants' motor systems were preoccupied with an unrelated motor task, the amount of change in visual sensitivity to dart throwing outcomes was attenuated. One interpretation of this result could be that the different types of motor input implemented in Experiment 3 partially disrupted the ability of the participant to simulate the observed dart throwing actions during the observation phase. An alternative explanation could be that participants can run multiple motor simulations at once and if doing so, the quality of either simulation is weakened. Recent work on joint motor coordination suggests that people can indeed run multiple motor simulations concurrently. Vesper and colleagues (2013) examined the joint coordination of two participants jumping unipedally at varying distances with the goal of synchronizing the landing times. During this task, participants could not see or hear their co-actor and only received feedback on the synchrony of their landings via auditory tone feedback. Participants did, however, have knowledge of how far they were expected to jump as well as how far their partner was expected to jump. The results revealed that if participants were expected to perform a shorter jump than their co-actor, the longer participants waited to jump in order to better synchronize with their partner. Furthermore, if participants were expected to perform a shorter jump than their co-actor, participants' jumps were temporally longer and spatially higher. The actions of participants in this study suggest that participants are simulating how long it will take the co-actor to achieve their jump and concurrently simulating how to modify their own jump to synchronize with their partner. As this relates to Experiment 3, an interesting possibility is that participants in the various motor pre-occupation conditions are simulating their own movements (whether they are actively or passively produced) while simultaneously simulating the dart throwing actions of the expert model.

As a result of executing multiple simulations, the quality of either simulation is partially sacrificed. Future research could examine this alternative explanation using a dart throwing task, similar to the paradigm employed by Vesper and colleagues (2013), in which participants are instructed to coordinate dart throwing with a model to targets of varying distances.

The motivation of Experiment 4 came from the common coding theory (Prinz, 1997), which posits that visual and motor representations of action share common codes and in turn links perception and action. In Experiment 4, participants in the “invisible arm” condition demonstrated the largest gain in visual sensitivity following the motor task, despite the initial predications. It may be the case that removing vision of the throwing arm during the dart motor task enhanced attention and acuity to kinesthetic feedback. In fact, there is research suggesting that blind individuals have enhanced tactile acuity. Grant and colleagues (2000) examined differences between blind and sighted participants in a tactile task related to Braille reading. Braille consists of a 6-cell, 3x2 rectangular matrix with dots in different patterns within the 6 cells to represent letters of the alphabet. In the tactile hyperacuity task, the stimuli consisted of two columns of raised dots. The first column (standard column) included three dots in a perfect vertical line. The second column (comparison column) also featured three raised dots, however, the middle dot was displaced various amounts to the left or right of the other two dots. Participants were asked to run the index finger down the standard column first, then the comparison column and report if the displaced dot in the comparison column was to the left or right of the other dots. The blind participants were able to discriminate smaller displacements than the sighted control participants, suggesting that the blind participants had better tactile acuity than the sighted participants.

Blind individuals also demonstrate superior tactile acuity to grooved surfaces as well (Goldreich & Kanics, 2003). The goal of this study was to examine whether blind participants do have enhanced tactile acuity as compared to sighted participants through a passive tactile task in order to better characterize the differences in performance. Blind and sighted participants were asked to discriminate the orientation of grooved surfaces, while the surface of the stimulus was being pressed against the participants' stationary index finger. In each trial participants responded if the stimulus pressed against the index finger consisted of vertical grooves or horizontal grooves. In addition, the amount of force used to press the stimulus against the finger was manipulated. The results showed that the blind participants again outperformed the sighted participants. Tactile acuity overall declined with increased age but was better overall when the stimulus was pressed more forcefully into the fingertip. The average tactile acuity of blind participants was that of sighted participants but 23 years younger.

This research provides support for the possibility that removing vision can improve tactile acuity and in the case of Experiment 4, possible to enhance awareness to kinesthetic feedback. However participants in Experiment 4 were sighted and in the previously conducted studies described above, blindness occurred years before testing. Kauffman and colleagues (2002) conducted a study to examine the role of visual feedback and motor feedback during Braille learning in sighted individuals. Half of the sighted participants were blindfolded for the duration of the five day experiment. The remaining half of participants were not blindfolded and remained sighted. All of the participants were tested on a Braille character recognition task on the day before visual deprivation began (baseline), on day three and the last day of the experiment. In this paradigm, pairs of Braille characters were passively pressed against participants' fingertips sequentially. Participants responded if the characters were the same or different. Blindfolded participants performed more accurately than sighted participants over the course of the experiment. The authors concluded that visual deprivation for five consecutive days results in the ability to better learning tactile differences between Braille characters. In other words, relatively short term visual deprivation can result in changes in tactile acuity. Thus, it is possible that in

Experiment 4, removing vision of the throwing resulted in enhanced tactile or kinematic acuity, although the participants were not visually deprived for five consecutive days.

Facchini and Aglioti (2003) aimed to determine if visual deprivation in a lesser amount of time would result in similar tactile acuity improvements. Two groups of sighted participants completed a tactile acuity task in three separate testing sessions within the same day. The tactile acuity task was the same passive orientation task described in Goldreich and Kanics (2003), in which grooved surfaces were pressed in the finger tip and participants were asked to report if the grooves were vertically or horizontally oriented. Each of the three testing sessions were 20 minutes long and throughout the first testing session all of the participants were blindfolded. After the completion of the first testing session, half of the participants removed the blindfold and waited 90 minutes for the next session in a normally lit room to avoid visual deprivation. The other half of the participants spent the 90 minutes between testing session one and two blindfolded to induce visual deprivation. Following the second testing session, all of the participants removed the blindfolds and waited 120 minutes in a normally lit room for the final testing session. This was employed to remove any effects of visual deprivation. The results showed that participants in the visually deprived group demonstrated enhanced tactile acuity in the second testing session, after short term visual deprivation, than participants in the other experimental group. In the final testing session, this effect was absent and both groups performed similarly at the tactile acuity task. This suggests that even brief short-term visual deprivation results in enhanced tactile acuity. In Experiment 4, participants were not visually deprived (e.g., blindfolded), however, they did not have vision of their throwing arm throughout the motor task. Removing participants' ability to see their arm while performing the dart throwing task may have enhanced tactile and/or kinematic acuity.

Although there are no studies to my knowledge that examine immediate differences in visual deprivation on tactile acuity, these studies lend support for the possibility that the limb occlusion manipulation could result in changes in motor acuity that influencing subsequent performance in the action prediction task, as observed in Experiment 4. If this is the case, future work should examine the influence of manipulating the amount of time participants perform tactile tasks while using the vision tunnel that occludes vision of the arms. Based on the work above, the longer the limbs are occluded, the more aware of the limb movement participants could become.

One of the unifying aspects of Experiments 3 and 4 is the lack of specificity in the various manipulations on predicting action outcomes. In Experiment 3, it appears as though different types motor preoccupation influence action simulation uniformly. Motor preoccupation, whether from the arms or feet, active or passive, all resulted in less change in visual sensitivity and accuracy for predicting dart throwing outcomes. However, it was not surprising that all of the groups showed some improvement in predicting action outcomes from the pre- to post-action prediction tasks, as during the observation phase, they observed the outcomes of individual dart throws in the expert video. In Experiment 4, on the other hand, it was quite surprising that all of the experimental groups improved at predicting action outcomes despite the type of motor task performed. First and foremost, these participants never saw the outcome of the observed dart throws and did not receive feedback about their performance throughout the action prediction tasks. Secondly, even participants that physically performed the basketball task improved at a similar rate to participants who physically performed dart throwing. This could suggest that performing a variety of different motor tasks could inform the visual system in the subsequent action prediction task, or this could mean that dart throwing and basketball share some common motor mechanism that was not accounted for.

As mentioned previously in the general discussion of Experiment 1 and 2, various sports may share similarities in motor mechanisms important in acquiring the skill or gaining expertise. Balance ability has been examined in athletes spanning a wide range of sports and skills

(Hrysomallis, 2011). Gymnasts were found to be the top performing athlete in terms of balance, followed by soccer players, swimmers and basketball players. Specifically, balance ability is not one of the first motor mechanisms that comes to mind influencing swimming performance, yet, swimmers outperformed basketball players. One type of athlete, on the other hand, who would appear to need superior balance ability is a baseball pitcher. In delivering the ball across home plate, the pitcher twists their torso and lifts their leg, balancing briefly on one leg before whipping the ball towards home plate. However, pitchers' ability to balance unipedally was not related to pitch accuracy. The point here is that dart throwing and basketball may share some common motor element, such as balance ability, that undergoes fine tuning during motor performance and enhances the ability to predict dart throwing outcomes. One possible element that dart throwing and basketball share is that they are both nonballistic aiming tasks, such that participants control the position the arm before tossing an object with the goal to put that object in a very precise place. To explore this possibility, future work should look at predicting action outcomes as a function of a variety of different motor tasks related and unrelated to aiming.

Chapter 6: Concluding Remarks

The overarching goal of this dissertation was to explore the relationship between the visual system and motor system as it relates to a real-world motor skill, dart throwing. The father of perception-action coupling, J.J. Gibson, was first to note the importance of the link between the visual and motor system relationship. Many researchers following in Gibson's experimental footsteps have posited that the visual system and motor system share common cognitive codes (Prinz, 1997; Hommel et al., 2001; Jeannerod & Jacob, 2005). The common coding theory is an exciting theoretical possibility as it explains a wide range of perception-action coupling phenomenon. Observational motor learning, or one's ability to learn a novel motor skill by observing a model (Carroll & Bandura, 1982; 1985), is thought to rely on shared cognitive resources between the visual system and motor system. Additionally, one's ability to predict the outcomes of observed actions is hypothesized to utilize one's motor system in a simulation process (Blakemore & Decety, 2001; Knoblich, 2008; van der Wel et al., 2013). Finally, the common coding theory is supported through research demonstrating that motor training in the absence of vision improves the visual discrimination of complex stimuli (e.g., Hecht et al., 2001). Although the common coding theory remains the most parsimonious theory regarding these different research findings, one pitfall of the common coding theory is that it does not make *specific* predictions regarding observational learning or predicting other's actions.

Two theories that do make specific predictions for observational learning and action prediction are the direct matching theory (Rizzolatti et al., 2001) and the action reconstruction theory (Csibra, 2008). Experiments 1 and 2 attempted to pit the direct matching theory against the action reconstruction theory in observational learning paradigms. These two experiments focused on the observational learning of dart throwing from either an expert or novice model, as the direct matching and action reconstruction theories make specific predictions regarding the best type of model to observe. Unfortunately the results of Experiments 1 and 2 could be explained by physical practice, not the observation of a model, and thus did not support either the direct matching or action reconstruction theories. Experiment 3 aimed to systematically characterize the action simulation process posited to occur during action observation as it related to the direct matching and action reconstruction theories. Again, the results did not specifically support either the direct matching or action reconstruction theories, but lent partial support to the more general common coding theory. The three motor system manipulations appeared to partially diminish participants' ability to simulate the observed dart throwing actions, as evidence by less improvement in the prediction of dart throwing outcomes. In sum, the three experiments meant to unequivocally test the direct matching and action reconstruction theories showed no evidence of either theory.

The aim of Experiment 4 was to examine the common coding theory more generally, as opposed to either the direct matching or action reconstruction theories. The results of Experiment 4 converged with the results of previous work, demonstrating that motor experience with dart throwing in the absence of visual feedback resulted in improved visual discrimination of observed dart throws. Taken in total, the current four experiments show no support for the more specific direct matching and action reconstruction theories, but some support for the common coding theory.

While previous research from the perception-action coupling field has been able to utilize these same observational learning and action prediction paradigms with extraordinary success, it brings to question why these paradigms failed to produce similar results in the current studies. A possible explanation is that previous research has used novel motor skills that were constrained or not ecologically valid (e.g., button presses, moving robotic arms). As such, the conclusions drawn from the paradigms exploring constrained motor tasks may provide weak or incomplete explanations for the actual processes occurring during observational learning or action prediction with ecologically valid motor tasks, such as dart throwing. Although previous research infers different conclusions, based on the four current experiments the direct matching and action reconstruction theories simply cannot explain the results. It may be the case that as these theories currently stand, they are too specific to explain all of the results in the perception-action coupling field. The more general common coding theory, on the other hand, could be adapted to encompass the results from perception-action coupling research for both simple and complex motor skills.

Of theoretical relevance for the common coding theory, our results in conjunction with previous research on observational learning with constrained tasks may be informative about the time course of creating a common coding foundation. In observational learning, the to-be-learned motor task is always novel and therefore the visual and motor "codes" of the task may not yet exist cognitively. For simpler, constrained motor tasks, the successful results of observational learning may reflect both the creation of the common coding foundation and the interaction of the visual and motor codes. If the observation of a model performing a to-be-learned motor task is to be informative to motor learning, then the visual and motor representations of that action most both exist. Thus, for simpler motor tasks it may be possible to create and utilize the visual and motor codes of a motor skill in a shorter amount of time and with less visual and motor experience. However, for more complex, real-world skills, like dart throwing, creating the foundation of common codes between the visual and motor representations could take longer and require more visual and motor experience. In the design of Experiments 1 and 2, our null results may reflect a lack of common codes and too little visual and motor experience. For future work, it is important to demonstrate that observational learning is not limited to simple motor tasks but extends to real-world motor skills. In order to achieve that, it is likely that more visual and motor experience is necessary.

On a related note, motor learning is often characterized by a learning curve in which there are sharp gains in motor performance early in learning and a plateau in motor performance later in learning (Newell & Rosenbloom, 1981). Observational learning may be most evident at an optimal point in this learning curve. For previously successful observational learning paradigms with simpler motor skills, reaching this theoretical optimal point may take less time and experience than with more complex skills such as dart throwing. However, it has not been specified where this optimal point in the learning curve would be and how this relates to defining early stages from late stages in motor learning. Early motor learning is more cognitively demanding than late motor learning (Anguera, Russell, Noll, & Seidler, 2007). Introducing a model to observe too early in motor learning, or in other words before the optimal point, may be ineffective as cognitive resources are already in use trying to perform the novel motor skill. This would be in line with our results from Experiments 1 and 2 as there were improvements in participants' dart throwing accuracy and precision in a relatively short amount of time, yet no observable differences based on model type. Late motor learning is not considered cognitively demanding, however, performance gains are relatively minimal at this point in learning. This may also not be an ideal time to observe a model perform a motor skill as there may not be as much room to improve after observing the model. Thus, for the observation of a model to be the most effective and result in the greatest observational learning effects, the optimal point in the motor learning curve likely exists in the transition from early to late motor learning. Future work should aim to measure where on the motor learning curve (Newell & Rosenbloom, 1981) the observation of a model is most beneficial. More specifically, for each participant, dart throwing motor performance could be tracked over the course of several days and once a participant reaches a midpoint in the learning trajectory, then the observation of a dart throwing model could be introduced. Over time and with many participants, it would be possible to measure where the optimal point for observational learning to occur exists.

Furthermore, once this optimal point is identified, then it may be possible to test the best type of model to observe for complex motor skills like dart throwing. Showing that there is an optimal point for observational learning demonstrates that creating the foundation of common visual and motor codes may take different amounts of time depending on the to-be-learned task and that common codes must exist before more specific theories like direct matching or action reconstruction are applicable. This future work examining the time course of motor learning also could have important implications for defining early and late stages of motor learning, which currently is ambiguous and undefined. Determining where the transition between early and late motor learning occurs could help motor learning research standardize the definition of early and late motor learning stages.

The results of the current experiments also seem to suggest that the roles of attention and body movement awareness are critical for motor learning and observational learning to be possible. In Experiment 3, the more attentive participants were of the expert model's dart throws, a greater change was revealed in the visual sensitivity to predicting dart throwing. By observing the dart throwing model's movements and the outcome of each dart throw, participants who were paying more attention may have been discriminating crucial elements of successful dart throws. Furthermore, in invisible arm condition for Experiment 4, the more participants were aware of their body movements during the motor task, the greater change that was observed in visual sensitivity to predicting dart throwing outcomes. This suggests that being aware of one's own body movements as it relates to motor performance could lead to attentiveness of a model's body movements and the resultant action outcome from different body movements. Currently, the common coding theory makes no specific predictions about the role of attention or body awareness in the coupling of perception and action.

As mentioned above, observational learning and predicting action outcomes may depend heavily on attending to critical components of observed movements and one's own body movements. In other words, attention may help bridge the gap between common visual and motor codes of actions. Previous observational learning studies do not specify whether participants are instructed on the crucial components of the to-be-learned motor skill. The simple motor skills featured these studies often only examine one crucial component of skills, such as timing or coordination of the limbs. As a result, previous work could be considered as examining the "spontaneous" emergence of observational learning to "one-component" skills. Real-world motor tasks likely use multiple components, making observational learning less likely to arise spontaneously in the same amount of time as simpler motor skills. For example, in dart throwing, a single dart throw requires components of throwing force, timing and limb coordination. Thus, the null results of the current experiments in part could reflect participants' inability to selectively attend to these crucial elements to dart throwing and as a result participants were not able to bridge the gap between the visual and motor representational codes. Although in Experiment 3 participants who were more attentive to the dart throwing model demonstrated more improvement in the action prediction task, we do not know what they were attending to. It is not clear if participants in fact were using information on when the model released the dart, the model's arm movement or simply the trajectory of the dart to response during the action prediction task. Furthermore, the critical components of various motor skills are likely to be task-dependent. Future work could use eye-tracking to examine where participants are attending when observing a model perform various motor skills. This could elucidate the relationship between attending to critical components of a motor skill and changes in predicting action outcomes or changes in one's own motor performance. Additionally, this may clarify the similarities between different types of motor skills. In the current experiments, basketball was used as a control condition because the task was different from dart throwing but similar visually. In fact, these two tasks may be too similar as they are both aiming tasks. Eye tracking could reveal that when participants attend to a critical component of aiming task in general (e.g., when the model releases the object) that this information informs subsequent performance.

In conclusion, although the results of the current experiments revealed more questions than answers regarding current theories, the future directions exposed are extremely important for evolution of the common coding theory and the future of motor learning research. Examining the time course of motor learning and when the observation of a model is most beneficial is an important next step to characterize how common codes for novel motor skills are developed and consequently utilized. Furthermore, the common coding theory currently makes no specific predictions regarding attention and body awareness during observational learning or action prediction. By adding an attentional component to the common coding theory, specific predictions about observational learning and action prediction are possible. In first modifying the common coding theory, future work may reveal that other theories examined in the current work, such as direct matching or action reconstruction, are supported for different motor tasks and in different contexts.

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Appendix A: Experiment 3: Action Observation Survey

Subject Number ______________

Please answer the following questions about your performance during throughout the study.

Part 1: Action Prediction Task #1

1. How accurate do you feel you were in guessing whether the darts "HIT" or "MISSED" the yellow area? (place X in one box)

Not at all accurate 0%	Slightly accurate 25%	Moderately accurate 50%	Very accurate 75%	Extremely accurate 100%

Part 2: Observation of the Dart Thrower

2. While watching the video of the model, how much time did you spend looking at the target? (place X in one box)

Never 0%	Rarely 10% of the time	Occasionally 30% of the time	Sometimes 50% of the time	Frequently 70% of the time	Most Always 90% of the time	Everytime 100% of the time

3. How important do you think it was to watch the model's arm during the video? (place X in one box)

Not at all important	Slightly important	Moderately important	Very important	Extremely important

4. While watching the video of the model, how much time did you spend looking at the model's arm? (place X in one box)

Never 0%	Rarely 10% of the time	Occasionally 30% of the time	Sometimes 50% of the time	Frequently 70% of the time	Most Always 90% of the time	Everytime 100% of the time

5. How important do you think it was to imagine yourself as the model during the video? (place X in one box)

Not at all important	Slightly important	Moderately important	Very important	Extremely important

6. While watching the video of the model, how much time did you spend picturing yourself as the model? (place X in one box)

Never 0%	Rarely 10% of the time	Occasionally 30% of the time	Sometimes 50% of the time	Frequently 70% of the time	Most Always 90% of the time	Everytime 100% of the time

7. While using the mini bike, how much force were you using to move the pedals (place X in one box)?

No force at all	Very little force	Moderate amount of force	Substantial force	A great deal of force

Part 3: Action Prediction Task #2

8. How accurate do you feel you were in guessing whether the darts “HIT” or “MISSED” the yellow area? (place X in one box)

Not at all accurate 0%	Slightly accurate 25%	Moderately accurate 50%	Very accurate 75%	Extremely accurate 100%

9. What about the video informed you about whether the dart throw would hit or miss the yellow area?

____

____

Appendix B: Experiment 4: Action Experience Survey

Subject Number _________

Please read and carefully answer the following questions about your performance throughout the study.

Part 1: Action Prediction Task #1

10. How accurate do you feel you were in guessing whether the darts "HIT" or "MISSED" the yellow area?

Not at all accurate 0%	Slightly accurate 25%	Moderately accurate 50%	Very accurate 75%	Extremely accurate 100%

Part 2: Motor Experience

11. When performing the motor task, could you see your arm? (circle one) **YES** **NO**

In the questions below, place an "X" in the box that best describes your opinion or experience.

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
3. How important do you think it was to be able to FEEL your arm movement during the motor task?					
4. How important do you think it was to FEEL your arm movement in order to get better at the task?					
5. How important do you think it was to be able to SEE your arm move during the motor task?					
6. How important do you think it was to SEE your					

arm move in order to get better at the task?					

	Never aware	Occasionally aware	Sometimes aware	Usually aware	Always aware
7. How aware were you of the FEELING of your arm movement when performing the motor task?					
8. How aware were you of SEEING your throwing arm when performing the motor task?					
9. How aware were you of how HARD YOU THREW the object during the motor task?					
10. How aware were you of your HAND PLACEMENT on the object during the motor task?					
11. How aware were you of WHEN YOU RELEASED the object during the motor task?					

In the questions below, please mark how much the specified information HELPED YOU IMPROVE at the motor task by placing an “X” in the appropriate box.

	Never helped	Occasionally helped	Sometimes helped	Usually helped	Always helped
12. Seeing where the object landed					

13. Seeing my arm					
14. Feeling my arm					
15. Seeing how hard I threw the object					
16. Feeling how hard I threw the object					
17. Seeing how I held the object					
18. Feeling how I held the object					
19. Seeing when I released the object					
20. Feeling when I released the object					

21. How much do you feel the motor task influenced your ability to correctly guess whether the darts "HIT" or "MISSED" the yellow area in the second action prediction task?

Not at all influential	Slightly influential	Moderately influential	Very influential	Extremely influential

Part 3: Action Prediction Task #2

22. How accurate do you feel you were in guessing whether the darts "HIT" or "MISSED" the yellow area? (place X in one box)

Not at all accurate 0%	Slightly accurate 25%	Moderately accurate 50%	Very accurate 75%	Extremely accurate 100%

23. What about the video informed you about whether the dart throw would hit or miss the yellow area?

____

____

22. If you had to guess, what do you think this experiment is looking at?

____

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EDUCATION

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Area: Visual Perception and Cognitive Psychology
Dissertation: *Bull's Eye-Hand Coordination: Visual and Motor Contributions to Observational Learning.*
Committee: Dr. Maggie Shiffrar, Dr. Vanessa LoBue, Dr. Gretchen Van de Walle, Dr. Eebie Tricomi, and Dr. Robrecht van der Wel.

M.A. Rutgers, The State University of New Jersey, Newark, September 2011
Area: Visual Perception and Cognitive Psychology
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B.S University of Massachusetts, Boston, May 2007
Area: Psychology
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SUMMARY OF INTERESTS

My research emphasizes the contributions of perception-action coupling on observational motor learning. Specifically, I study the ability of individuals to learn a novel motor skill by observing novices and experts. Further, my research interests focus on changes in the accuracy of predicting action outcomes by manipulating visual or motor feedback during action observation. For example, my dissertation research aims to determine if active or passive motor input during action observation results in changes to correctly predict an action outcome. The inspiration for my dissertation research came from teaching children gymnastics and developing instructional methods to encourage motor development, which would serve as a future research interest of mine. Lastly, my instructional interests focus on sharing my own enthusiasm for experimental methods with students and developing critical thinking skills.

WORK EXPERIENCE

2004-2008 The Little Gym, Medway, MA
Pre-K and Grade School Gymnastics Instructor, Dance Program Director

AWARDS AND HONORS

2013 Lehrman Fellowship, Rutgers University, Newark.
2011 Teaching Assistant of the Year Award, Psychology Department, Rutgers University, Newark.
2009 Lehrman Fellowship, Rutgers University, Newark.
2009 NSF Graduate Research Fellowship Award Applicant. Status: Not Funded
2007 Adrian Jill Barnett Memorial Prize, University of Massachusetts, Boston. Status: Funded

RESEARCH EXPERIENCE

2012 – Present Rutgers, The State University of New Jersey, Newark
Visual Cognition Laboratory
Principal Investigator: Dr. Maggie Shiffrar
Research Topic: Contributions of the visual and motor systems on observational learning of dart throwing.

2009 – 2012 Rutgers, The State University of New Jersey, Newark
Visual Cognition Laboratory
Principal Investigator: Dr. Maggie Shiffrar
Research Topic: Visual sensitivity to threat-related emotional body postures.

2006 – 2007 University of Massachusetts, Boston
Visual Perception Lab
Principal Investigator: Dr. Erik Blaser
Research Topic: Perceptual learning and visual discrimination of gradients.

2005 University of Massachusetts, Amherst
Department of Psychology
Principal Investigator: Dr. Elliott Blass
Research Topic: Influences of media on eating behavior in college students.

CONFERENCE PRESENTATIONS

Blanchard, A. K., Schapell, A., Thomas, J.P., Shiffrar, M., & Boxer, P. (2012). Emotion perception of recently incarcerated males. *Presented at the Vision Sciences Society annual meeting, Naples, FL.*

Blanchard, A. K., & Shiffrar, M. (2011). Does the threat advantage hypothesis extend to static body postures? *Presented at the Vision Sciences Society annual meeting, Naples, FL.*

Blanchard, A. K., & Shiffrar, M. (2010). Enhanced visual detection of threat-related emotional body postures. *Presented at the Object Perception, Attention, and Memory (OPAM) annual conference, St. Louis, MO.*

Blanchard, A. K., & Shiffrar, M. (2010). The visual recognition and detection of emotional body postures. *Presented at the Annual Scientific Meeting of the Psychonomic Society, St. Louis, MO.*

TEACHING EXPERIENCE

Courses Taught at Rutgers University, Newark
PYSC 302 Experimental Methods for the Cognitive and Behavioral Sciences, Summer 2012

Courses Taught as a Teaching Assistant at Rutgers University, Newark
PSYC 101 Principles of Psychology, Fall 2010 & Spring 2011, Dr. Maggie Shiffrar
PSYC 101 Principles of Psychology, Spring 2013, Dr. Allyson Meloni
PSYC 301 Statistics for the Cognitive and Behavioral Sciences, Fall 2011, Dr. Dan DePaulo
PSYC 301 Statistics for the Cognitive and Behavioral Sciences, Fall 2012, Dr. Ellen Halpern
PSYC 302 Experimental Methods for the Cognitive and Behavioral Sciences, Spring 2010 & Spring 2012, Dr. Harold Siegel

EDITORIAL EXPERIENCE

Ad hoc reviewer for the professional journal, *Visual Cognition*.

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Graduate Applicant Mentor, Psychology Department, Rutgers University, 2013
Psychology Department Representative (peer-elected), Graduate Student Government Association (GSGA), Rutgers University, 2011 – 2012
Committee for Research on Qualifying Exam Revisions, Psychology Department, Rutgers University, 2011

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Vision Science Society
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