Learning-Model Action Observation

An Investigation in Long-Term Motor Learning Outcomes

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Table of Contents

List of Tables

List of Figures

Abstract

Early motor learning is driven by error commission and feedback during physical practice (PP). Motor learning can also be facilitated by action observation (AO), which classically involves observing a skilled model flawlessly complete a skill. To determine whether error-dependent feedback is conserved in AO, participants were recruited to learn a dart-throwing task via AO and PP. Over a 6-week period, participants observed either a learning model, who commits and corrects errors, or a skilled model committing no errors, followed by PP of the task. Participants' performance on both the primary task and a transfer task was measured and contrasted to determine which AO model resulted in better motor learning. Results indicated that while the learning model group generally performed better on both tasks, the difference was not significant, suggesting that learning model AO may not be superior to skilled model AO in long-term motor learning.

List of Abbreviations Used

AO: action observation

ERN: error-related negativity

LME: linear mixed effects

LMG: learning model group

MI: motor imagery

MNS: mirror neuron system

MRE: mean radial error

PP: physical practice

SMG: skilled model group

STS: superior temporal sulcus

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Chapter 1: Introduction

Motor learning refers to the process by which one acquires, develops, and refines motor skills (Newell, 1991). Given that motor skills are critical facets of activities of daily living, recreation, athletics, and occupational settings, an improved understanding of the processes underlying and driving motor learning can contribute to accelerated motor skill acquisition across a wide variety of fields. During the earliest phases of acquiring a novel motor skill, there is a high degree of dependence on error commission and correction; namely, an individual must make errors and derive feedback from multiple task attempts to consolidate learning of a new motor skill (Seidler et al., 2013).

While motor learning is classically driven through physical practice (PP) of the skill one is trying to learn, a number of alternate learning strategies exist. One such example is action observation (AO), which involves watching another individual perform a motor skill, driving learning of that same skill. AO is facilitated through the body's mirror neuron system, a set of neurons with complex firing patterns that activate the same sensorimotor pathways when observing a movement as would be activated during physical execution of that movement (Keysers et al., 2003; Wolpert, Diedrichsen, and Flanagan, 2011). These pathways activate the same neural structures and cytoarchitecture involved in performing the skill (Sale and Franceschini, 2012), enabling an alternative to PP that may be more accessible for individuals during rehabilitation of an injury or disease, or in circumstances where fatigue, time, or resources limit PP opportunities. While notable that independent PP generally yields better motor learning outcomes as compared to independent AO, a combined dosage of PP and AO results in superior motor skill acquisition as compared to either strategy used independently (McNeill et al., 2019).

Conventionally speaking, AO involves observation of a skilled model who flawlessly executes the task being demonstrated. However, this approach does not capitalize on the significance of error correction and feedback-driven learning cycles, both of which are critical drivers of early motor learning (Seidler et al., 2013). In comparison, AO of a learning model who commits errors during observation and improves their performance over time may be a more optimal alternative for early-phase learners who depend more heavily on feedback to drive skill acquisition. Despite a robust base of literature and conceptual predictions indicating that learning-model AO likely has benefits over skilled-model AO during early learning, attempts to demonstrate this effect remain limited and inconclusive (McCullagh and Meyer, 1997; Weir, 1988; Pollock and Lee, 1992). One potential contributor to these findings may be the relatively low AO and PP volumes used in these studies, which generally did not exceed more than two sessions of participant training. Given that motor learning through PP takes weeks, months, and even years to acquire and consolidate feedback (Nieuwboer et al., 2009), it is reasonable to presume that the mechanisms driving AO would likely need to be active for similar levels of time as they would in PP.

This work aimed to address the question of learning- versus skilled-model AO using a longitudinal study design wherein participants trained a dart-throwing task over a 6-week period using AO and PP. All participants completed the same volume of AO and PP (approximately 1,200 throws of each), with the difference between experimental groups being the model they observed: either a learning model, who initially demonstrated multiple errors in their dart throw and improved over time, or a skilled model, who initially demonstrated very few or absent errors in their dart throw and did not vary in performance over time. It was hypothesised that AO of the learning model would lead to both superior motor skill acquisition and transferability as compared to AO of a skilled model.

Interested individuals were determined to be eligible to participate if they were right-handed, over the age of 18, had normal vision and no conditions that would prevent them from learning a novel task, and were considered novice to dart-throwing tasks. The lattermost point was considered significant in that novice individuals were predicted to be the most likely responders to learning model AO given their dependence on errors and feedback during early-phase learning (McNeill et al., 2019). Eligible participants completed a total of 18 sessions, inclusive of an introductory session involving consent and a 15-throw pretest. Subsequent sessions involved AO of the model completing 75 dart throws, interspersed with 75 physically-practiced dart throws by the participant. Motor skill acquisition was measured using the mean radial error (MRE) of the participants' distance from the target of the dart-throwing task, the bull's eye. On participants' final sessions, the task was modified such that five unique points on the dart board became the new targets, with the distance of the dart from these points being a measure of motor skill transferability.

Motor skill acquisition was analyzed using a linear mixed effects model, and motor skill transferability was analyzed using an independent t-test. While both measures were slightly superior in the learning model group compared to the skilled model group, the differences were not significant at the 95% confidence level. The results of this study imply that while coupling PP with learning model AO is an effective approach to learning a novel motor skill, there is no evidence to support that it leads to significantly better acquisition or transferability compared to skilled model AO. These findings enhance the collective understanding of motor learning theory and fundamental neuroscience and may have valuable implications in the fields of athletics, occupational training, and rehabilitation following disease or injury.

Chapter 2: Background

2.1 Relevance and justification

Motor learning is the process by which one acquires, develops, and refines a **motor skill**, a term generally referring to a coordinated physical effort involving a sequence of movements to achieve a particular goal or outcome (Newell, 1991). Motor skills range from basic activities of daily living such as brushing one's teeth or getting dressed, to occupational tasks like manual labour or tool handling, or to performance-oriented athletic outputs such as throwing, striking, jumping, or running. Wherever a motor skill is implemented, it is necessarily preceded by the *learning* of said motor skill, which can occur at various stages and settings throughout one's lifespan, be this early childhood, old age, recreation, or work. Furthermore, motor learning holds a special place in the field of rehabilitation, where it is the primary approach in the re-acquisition of motor skills following surgery, brain injury, or diseases such as stroke (Krakauer, 2006). Given the pivotal role that motor skills play in day-to-day activity across all walks of life and levels of human function, research in **motor control** – the study of movement planning and execution (Schmidt et al., 2018) – has been concerned with understanding the processes involved in motor learning. By better understanding the factors driving these processes, key elements may be prioritised and leveraged to lead to better, faster motor skill acquisition outcomes.

Accelerated motor learning presents a number of advantages for the numerous settings involving motor learning. For instance, faster motor skill re-acquisition during rehabilitation could lead to swifter patient recovery times and reduced demands on limited healthcare resources. In performance and athletic environments, rapid motor skill acquisition can make efficient use of the limited training time available during a season, either affording a greater amount of effective training time – namely, time spent contributing to context-relevant motor skill development – or freeing up time resources to pursue different training aspects. Faster development and acquisition of motor skills in occupational settings could lead to reduced monetary and time costs in employee training and may result in fewer workplace errors. This type of process optimisation offers clear and numerous benefits but is necessarily preceded by an understanding of the processes driving motor skill acquisition.

2.2 Motor learning principles, processes, and error-based learning

Motor skills are composed of fixed sequences of movements (Hikosaka et al., 2002), and are typically improved and consolidated in the body through repetition and practice (Karni et al., 1998; Brem, Ran, and Pascual-Leone, 2013; Luft and Buitrago, 2005). This process of improvement occurs in three broadly-defined stages, as first described by Fitts and Posner (1967): firstly, the **cognitive stage**, where movements are slow and consciously deliberate; secondly, the **associative stage**, as movements become more fluid and autonomous; and lastly, the **autonomous stage**, where movements are fully autonomous and require little conscious input to successfully accomplish (Karni et al., 1998; Marinelli et al., 2017; Weaver, 2015; Nieuwboer et al., 2009). The associative stage may often be thought of as an intermediate phase between **early-phase learning**, which tends to be faster and elicits larger changes in skill level, and **late-phase learning**, which is often slower and is characterised by incremental changes and fine tuning of the skill (Karni et al., 1998; Marinelli et al., 2017). The earlier phases tend to be more cognitively demanding and uncoordinated compared to later phases and are characterised by the commission and correction of errors when attempting to execute the skill being learned (Seidler et al., 2013). Over time, practice of the skill leads to a higher proficiency in the skill –

efforts become more autonomous, fewer errors are made, and applying the motor skill to accomplish a given task requires less conscious input (Nieuwboer et al., 2009).

While proficiency in a particular motor skill is characterised by a relatively small rate of error commission, it is preceded by the commission and correction of errors in the first place. In fact, the process of **trial-by-trial error correction** is a significant driver of motor learning, particularly in the early phases when numerous errors are committed (Nieuwboer et al., 2009; Seidler et al., 2013), and can be roughly described as follows. Prior to attempting a motor task, the body's sensorimotor system takes note of a number of pieces of information, including the initial state of the environment and the pre-response state of the musculature, and uses them to estimate the optimal strategy or **motor plan** for task completion. During and after the task's execution, the sensorimotor system evaluates the dynamics and trajectory of the task-relevant effectors, as well as objective and subjective information about the task outcome, and compares these to the estimated motor plan in the form of an error signal. This error signal is used to improve future estimates of the appropriate motor plan for subsequent task attempts (Diedrichsen et al., 2010).

A perplexing aspect of the above process is that the time to generate sensory error information, process it, and incorporate it into a corrected subsequent task attempt – around 120-200ms in duration – is far slower than the time taken to carry out these corrected movements in real time. To explain the reason for this discrepancy, Schmidt (1975) drew on an idea first proposed by Lashley (1917) that these movements were decided upon prior to the movement being initiated and were centrally controlled by sets of stored muscle commands "primed" for action at any time called **motor programs**. Schmidt reasoned that there existed generalised motor programs for given classes of movements (e.g., throwing tasks) from which one is selected to meet the demands of the task at hand – in other words, there is not a one-to-one match between the various stored motor programs and all the specific movements an individual can produce. Given that not all tasks within a class of movement are identical to one another (e.g., throwing a dart at a nearby board requires a different approach than throwing a baseball to a distant catcher), information about the environment and pre-response state are used to estimate the appropriate **response specifications** to modify the selected motor program. The correct determination of these parameters allows the performer to appropriately adapt their motor program to the task at hand and select the correct movements for a successful attempt.

In what would come to be known as **schema theory**, Schmidt goes on to describe that following the execution of a movement, four pieces of information are assessed and stored: 1) the pre-response state of the relevant musculature and the environment, 2) the selected response specifications for the program, 3) the objective sensory consequences of the produced response, and 4) a subjective interpretation of how successful the response was in completing the task. This lattermost piece of information can also be thought of as the performer's **knowledge of results**, a key determinant in the trial-by-trial error correction process described above – without any sort of task-relevant feedback, the performer cannot know if their effort was successful or not, and does not have the necessary signal to modify their response specifications appropriately.

Wolpert, Miall, and Kawato (1998) proposed a novel computational framework in which motor programs were organised, selected, and engaged using controllers known as **internal models** – state-dependent sensorimotor representations of the task's response specifications as estimated by the sensorimotor system (Thoroughman and Shadmehr, 2000). Internal models are thought to be mainly housed in the cerebellum (Imamizu et al., 2003; Ito, 2008; Wolpert, Miall, and Kawato, 1998), a region of the brain also generally involved in error-based learning processes (Wolpert, Diedrichsen, and Flanagan, 2011; Seidler et al., 2013; Butcher et al., 2017; Petrosini et al., 2003), and can be categorised into two related subtypes. An **inverse model** initially identifies the appropriate motor program, as proposed by Schmidt, and associated response specifications necessary to complete the task, based on prior experiences, expectations, and perceptions of the state of the task environment. Once the task itself has been attempted, the comparison between the actual outcome and the intended outcome prescribed by the inverse model is recorded (Miall, 2003). This comparison is used to inform and develop a **forward model**, which estimates the outcome that a particular motor plan will yield for a particular motor task based on the body's prior experiences with said plan and task (Cooper, 2010). In this way, the two internal models act cyclically with one another, generating sensory feedback with each action-outcome iteration to refine and eventually grasp the estimated motor plan required for a successful task outcome (Pickering and Clark, 2014; Wolpert, Diedrichsen, and Flanagan, 2011). This proposition integrated elegantly with elements of Schmidt's schema theory while elucidating on the specific mechanisms used to access and utilise the information stored after each movement execution. Well before the advent of these theories, MacNeilage and MacNeilage (1973) unknowingly summarised this process and goal with the notion that "the need for peripheral sensory feedback can be thought of as inversely proportional to the ability of the central nervous system to predictively determine every essential aspect of the following acts.".

Capitalising on this type of error-based correction mechanism requires a **signed error signal** to adjust the motor plan in the proper direction. This requires not only the knowledge of the task results as proposed by Schmidt, but also a further understanding of the ways in which it fell short (Wolpert, Diedrichsen, and Flanagan, 2011). For instance, a dancer who attempts a jump with a certain height in mind but does not jump high enough not only recognises that her jump was unsuccessful but acknowledges that on a subsequent attempt she must adjust her motor plan to jump *higher*, not lower. Depending on the dancer's familiarity with the task, the adjustments for a successful next attempt may be understood generally (e.g., to push off from the floor with greater force) or specifically (e.g., to engage the core and heels during propulsion to achieve this greater force). This moment of recognizing and processing a committed error generates a neurophysiological signature that can be recorded via electroencephalography. When an overt motor error is committed, an event-related potential is produced approximately 100ms following the actual commission, known as an **error-related negativity (ERN)** (Gehring et al., 2011). The ERN is produced in the **anterior cingulate cortex**, a region of the brain involved generally in motor control and specifically in adapting behaviour to changes in state and task demands. Larger ERNs are evoked when larger errors are committed, while smaller errors manifest in smaller ERNs. Both the magnitude and the relative abundance of ERNs have been shown to decrease as motor learning advances from earlier to later phases, as the motor skill becomes more autonomous and approaches proficiency (Seidler et al., 2013).

2.3 Action observation theory and the mirror neuron system

It has been established that motor skills are generally improved by repetition and practice, but this practice does not necessarily need to involve physically performing the skill in question. Motor learning can be facilitated by **action observation (AO)**, the process of observing another perform a particular action. This process utilises the body's **mirror neuron system (MNS)**, a group of neurons that discharge similarly when observing an action as they do when performing the same action (Oztop, Kawato, and Arbib, 2013; Wolpert, Diedrichsen, and Flanagan, 2011; Mattar and Gribble, 2005). Mirror neurons demonstrate highly complex firing patterns: they respond to anticipations of visual, auditory, and tactile stimulation associated with a particular action (Keysers et al., 2003), and will activate the sensorimotor pathways involved when observing a goal-oriented task even if stages of that task are not clearly sensible (e.g., observing a hand reaching for an out-of-sight object) (Miall, 2003). The firing pattern appears to occur in a predictive manner, implicating the involvement of learned priors and expectations related to the specific action being observed (Flanagan and Johannson, 2003). This facet is necessarily preceded by the involvement of a specific action or task's forward model(s), based on the expectations and anticipations of the sensory feedback present during that action's outcome (Kirsch and Cross, 2015).

During AO of a particular task, the observer's neural structures involved in physically performing the observed task are activated (Sale and Franceschini, 2012; Fadiga et al., 1995). The observation process generates and refines a sensorimotor representation of an observed action similarly to how a representation is generated and refined during repeated physical execution of a motor skill (Wolpert, Diedrichsen, and Flanagan, 2011). These shared characteristic processes give rise to the notion that there exists a **functional equivalence** between the observation of an action and the actual performance of that action (Holmes and Calmels, 2008; Jeannerod, 2001). This notion forms the basis for the fact that learning of a motor skill can be facilitated by virtue of the MNS-induced activation of the same neural structures and pathways involved in the physical execution of that skill (Mattar and Gribble, 2005; Wolpert, Diedrichsen, and Flanagan, 2011; Stefan et al., 2005). Following from this, AO can be effectively applied to a variety of motor learning environments. Cross et al. (2008) demonstrated that individuals who simply watched an actor correctly perform a motor task achieved higher task performance scores than individuals who did not watch the actor. With this being said, there are a number of key contrasts between AO and physical practice (PP). Previous work has indicated that compared to PP, learning via AO appears to be modulated by the frequency at which learners are informed whether the task was successful or not, implying a more perceptual dependence in AO compared to PP (Badets and Blandin, 2010). Cross et al. (2008) also concluded that individuals who solely physically practiced a motor skill had higher task performance scores than individuals who solely observed the skill being correctly performed, implying that PP is a more potent learning strategy compared to AO when available.

However, numerous studies have found that the **combination of AO and physical practice of a task (AO+PP)** will result in better performance outcomes and greater task motor memory than solely PP or solely AO. Based on the motor simulation performance model proposed by McNeill et al. (2019), this effect is most pronounced when utilised by lower-skilled individuals: namely, those who are inexperienced in the motor skill being learned or trained. However, AO+PP still leads to greater performance changes for moderately- and highly-skilled individuals, albeit with a smaller difference than that seen for lower-skilled individuals. This effect has been demonstrated in the rehabilitation of stroke (Sugg et al., 2015; Celnik et al., 2008; Sale and Franceschini, 2012), cerebral palsy (Kim, Kim, and Ko, 2014), and Parkinson's disease (Pelosin et al., 2010), as well as in behavioural and sequence task learning (Mattar and Gribble, 2005; Kelly et al., 2003) and human performance (Holmes and Calmels, 2008; Calvo-Merino et al., 2005; Neuman and Gray, 2013). These case studies suggest that combining PP and AO has a mechanistically constructive effect and can accelerate and improve motor learning in a broad variety of learning environments.

2.4 Optimising AO as an approach to motor learning based on motor control theory

A common feature of note in the vast majority of studies and environments that have used AO as a motor learning strategy, whether alone or in combination with PP, is that the observed action tends to resemble or closely resemble a perfect execution of the motor skill being trained – namely, the model executing the observed action is skilled at the task (Neuman and Gray, 2013; Calvo-Merino et al., 2005; Hari et al., 1998; Pelosin et al., 2010). Skilled model AO gives a clear portrayal of the goal of the motor task in question, and the correct conditions that accompany success – relevant facets for both motor learning, as per Wolpert, Diedrichsen, and Flanagan, 2011, and AO-induced neural activation, as per Miall, 2003 – but there is evidence to suggest that this approach does not fully optimise AO as a motor learning strategy. An individual's ability to interpret and process another actor's actions during AO of a motor skill can depend on the observer's own prior experience with said skill, or its use in completing a motor task. An individual in the early phases of motor learning may have difficulty identifying and replicating components of a skill relevant to task success, simply due to their unfamiliarity with the skill and task alike (Wolpert, Diedrichsen, and Flanagan, 2011). This is particularly relevant given that, as per McNeill et al. (2019), AO appears to have the greatest effect in performance changes for early-phase learners – in other words, those who can learn the most from AO are likely to be unfamiliar with the skill or task at hand. This suggests a possible disjoint in the application of AO as a learning strategy and the population of learners to which it most effectively applies.

Furthermore, it has been proposed that observing repeated perfect performance of a motor task promotes "mimicry" of an ideal motor task outcome (Lee, Swinnen, and Serrien, 1994). This may be thought of as akin to studying for a test by memorizing the answer key – it can equip the learner for a successful outcome in one very particular task environment, but this strategy may not afford a full grasp of the minutiae and subject matter of the actual learned material. In classical structural learning theory, an appreciation of the design, parameters, and environmental context of a particular motor skill allows an individual to adapt to changing task circumstances and dynamics. Individuals exposed to a series of motor tasks similar in structure but with randomly varying parameters tend to adapt quickly to tasks throughout the series, based on their familiarity with the possible perturbations in the task goal (Wolpert, Diedrichsen, and Flanagan, 2011). If individuals learning via skilled model AO are exposed only to a narrow swath of possible task parameters – i.e., those associated with expert performance of a skill, such as repeatedly and flawlessly sinking a three-point basketball shot from a certain point on the court – they may be disadvantaged when adapting the skill to different task environments, having not been familiarised with variations to the task dynamics.

Fitts and Posner proposed that the early phases of motor learning are driven by the commission and correction of errors to refine the sensorimotor system's internal models. A brief examination of the mechanisms driving AO illustrates a similar involvement of – and even dependence on – error generation to drive motor learning. In accordance with the notion of functional equivalence between PP and AO (Holmes and Calmels, 2008; Jeannerod, 2001), there appear to be a number of hallmarks of error-based learning associated with PP that are conserved when using AO as a motor learning strategy. There exists evidence that humans are capable of recognizing, processing, and learning from motor errors made by other individuals (Burke et al., 2010). The error-processing network involved in processing self-generated motor errors appears to also be engaged during motor error observation (Wolpert, Diedrichsen, and Flanagan, 2011), suggesting that the mechanisms involved in garnering sensory feedback from a self-generated error are similarly employed during error observation. Furthermore, numerous studies have indicated that an ERN is similarly produced when an observer witnesses and recognises another individual making a motor error (Koban et al., 2010; Luu, Tucker, and Makeig, 2004; Thanh et al., 2014; Bates, Patel, and Liddle, 2005).

The conservation of these identifiable physiological hallmarks lends credence to the proposed hypotheses surrounding potential mechanisms driving AO error-based learning. Wolpert et al. (2003) suggested that the body's internal models for a particular motor skill or task can be meaningfully updated in real-time using feedback from observed errors. Given the similarities in sensorimotor systems between humans, the authors suggest that an individual observing a particular motor task can understand which muscles are activated and engaged and can detect adjustments to muscle engagement and dynamics as errors are committed and corrected. This process of observing the processes and outcomes of another individual's actions may provide enough feedback to refine the observer's internal models and drive motor learning, at least partially. Miall (2003) goes further to propose a hypothesis involving the mirror neurons located in the superior temporal sulcus (STS) and their ability to provide feedback for internal model refinement. It is suggested that a visual representation of an observed action is generated by the mirror cells in the STS and is relayed to the posterior parietal cortex (PPC) and mirror cells in the F5 area of the ventral premotor cortex. Projections leading from F5 and the PPC may be implicated in relaying information to the cerebellum, an area of the brain not only involved in error-based motor learning via PP and considered to be the storehouse of the body's internal models (Petrosini et al., 2003), but also demonstrated to be an active element of the AO network (Sokolov et al., 2010). The mechanism proposed by Miall (2003) elegantly links error feedback acquired by AO directly to the region of the brain mostly likely involved in processing observed feedback, illustrating how motor skill representations may be improved in AO.

Both the evidence and hypotheses discussed above illustrate a convincing precedent that humans can identify, process, and learn from observed errors in the same way that they learn from self-generated errors, and that AO has the potential to utilise error commission and correction as a resource in motor learning. Within this paradigm it becomes quickly apparent that using a skilled model to facilitate learning via AO could be potentially disadvantageous to the learner, in the sense that a skilled model neither commits nor corrects errors. If a learner can develop a motor skill or task simply by watching another actor make and correct errors, there exists an avenue by which to accelerate AO-based motor learning. This promising outlook could reduce the number of errors that a learner would need to make during their own PP of a skill or task, given that the actor's error commission-correction cycles would generate sensory feedback and correction information for the observer to then use to update their own internal models – in a way, the actor makes the errors "for" the observer. As a result, the observer could achieve motor skill fluency faster, and with less physical practice of the skill itself, leading to reduced time and resource costs in motor learning environments.

2.5. Previous research and the role of task exposure volume

There have been attempts by some previous studies to demonstrate that, when paired with PP, using a learning model in AO leads to better motor skill outcomes than the use of a skilled model. Pollock and Lee (1992) used a computer tracking game that had previously shown a large effect as an experimental motor task when participants observed a learning model. Two groups, each consisting of 18 female participants who were novice to the tracking game, participated in task learning via AO of either a skilled or learning model completing the game.

The skilled model group observed the experimenter perform the task, while the learning model group observed the other participants perform the task (i.e., they observed models who were fully novice to the task and were authentically learning the task as they were observed). Participants received a verbal description of the task, observed their respective model perform 3 trials of the task, and then performed 3 trials themselves. They then observed the model complete another 12 trials, followed by completing another 12 trials themselves, to conclude their study participation. Comparisons between the results of the two groups indicated that, while observation of a model led to improvements in performance against a control group who did not observe any model, there was no significant difference in performance gains – as measured by the number of errors committed in the task – based on whether they observed a learning or skilled model.

Work by McCullagh and Meyer (1996) compared the effectiveness of skilled and learning model AO by training 40 female participants on a free-weight squat lift with a 25lb barbell. This study also addressed the effect of providing feedback to participants, and how it might interact with the skill level of the model they observed. This feedback was presented by the study facilitators in one of two ways: as knowledge of performance, wherein a controlled number of comments were made on the participant's squat kinematics and technique, and as knowledge of results, wherein the participants were told the outcome of their performance (in this case, the number of squats they completed during each of the five trials). The participants were assigned to one of four training conditions – observation of a learning model without feedback, observation of a learning model with feedback, observation of a skilled (or correct) model with feedback, and a control group that observed no model and received feedback. In addition, the control group acted as the model for the two learning model groups, once again representing an authentic learning progression by employing a similar technique to the one used by Pollock and Lee (1992). The participants, none of whom had experience performing a squat, would perform five 30-second acquisition trials with a 2-minute rest between trials, during which they completed the squats. Before beginning their first trial and during the rest period between each of the trials, participants viewed their group's respective model perform the task. As noted above, the feedback groups received commentary on both their performance and results from the experimenters. After two days had elapsed following the five-trial session, the participants returned to perform three 30-second trials with a 2-minute rest interval, but without any feedback or model observation. These three trials were used to evaluate participants' performance on the task based on 12 criteria related to squat performance. Similar to the work completed by Pollock and Lee (1992), the results indicated that observing a model led to better learning outcomes than the control group; furthermore, it was also found that groups in receipt of feedback had improved learning outcomes compared to the group that did not receive feedback on their performance nor results. However, no significant difference in performance outcomes independent of feedback receipt was found between the two modelling conditions, implying that viewing either a correct or learning model was equally effective for the task at hand.

The conclusions of both Pollock and Lee (1992) and McCullagh and Meyer (1996) are incongruent with the physiological and behavioural bases and conceptual predictions supporting the advantages of using a learning model in AO protocols. Weir (1988) attempted to demonstrate these advantages by utilising a dart-throwing task wherein participants would observe either a learning model or skilled model, and then physically attempt the task themselves for 60 throws. Thirty right-handed females were recruited and assigned to one of six groups consisting of five participants each: AO of a skilled model with knowledge of results (meaning the participants knew the result of their observed model's throw), AO of a skilled model with no knowledge of results (meaning that the participants did *not* know the result of their observed model's throw), AO of an unskilled model with knowledge of results, AO of an unskilled model with no knowledge of results, and two control groups, one completing 60 PP throws and the other completing 68 PP throws, with no model observation. Participants in the model groups observed kinematic footage of their respective model throw eight darts. Each throw was separated by a 20-second interval, during which the knowledge of results and no knowledge of results groups were shown a blank screen. Neither control group observed models completing the throws, but the 68-throw group completed 8 throws during the observation period to account for potential differences in task volume exposure between the control and observation groups. Following the observation period, all groups then completed 60 throws with knowledge of their own results; following a 24-hour retention interval, all participants completed four additional throws, without knowledge of their own results.

When examining the independent effects of the model's skill level and the knowledge of results factors between groups, the author found that participants who observed a learning model achieved a lower absolute constant performance error than those who observed a skilled model, suggesting that those who observed a learning model had achieved better learning outcomes than those who did not. It was surmised that participants were likely able to derive more meaningful information from the variable performance of the learning model, as compared to the uniform performance of the skilled model. However, this difference was only apparent when comparing the no knowledge of results learning and skilled model groups. When assessing the difference between the knowledge of results learning and skilled model groups – namely, those two groups that knew the outcome of their model's throw – it was found that the skilled model group had a slightly higher performance than the unskilled model group, though the difference was not significant. This result has implications on differentiating between observation of variable task performance and erroneous task performance, and the importance of having knowledge of results to drive learning as per McCullagh and Meyer (1996). Without knowledge of results, the participants' perception of their observations was that the model was either using consistent kinematic strategies, in the case of the skilled model, or variable kinematic strategies, in the case of the learning model, to complete the task. It was then the up to the viewers' discretion as to how these strategies were interpreted, allowing for selective emphasis or disregard of certain techniques and resultant incorporation into their own internal models to drive learning. Meanwhile, those observers with knowledge of results would be able to link these variable kinematic strategies with information regarding the relative success or failure of the task, instantly receiving an impression of which kinematic strategies resulted in task failure and which resulted in task success. This information can be thought of as analogous to Schmidt's proposition of the information stored after an overt task execution, and likely plays a similar role in informing subsequent task attempts. In any case, the results of this study complement the robust literature base and conceptual predictions indicating a probable link between model skill level and observers' performance outcomes, setting a precedent for further exploration in this area.

One factor that seems to have gone uninvestigated in these studies is the volume of training the participants underwent. Training volume never exceeded more than two sessions in the listed studies, with a second session – if present – acting as a retention trial to observe how learning was preserved. Given the indication that AO bears a functional equivalence to PP as a motor learning strategy, it is not unreasonable to postulate that the mechanisms driving learning via AO should be active for similar volumes of time or task exposure as they would be during learning via PP to achieve the same level of motor skill proficiency. In PP, a certain amount of training volume – broadly used here to describe time, training effort, or number of task iterations – must be spent in the early phases of learning before advancing to a more autonomous, fluid proficiency of the skill (Nieuwboer et al., 2009; Seidler et al., 2013). For an individual truly novice to a new motor skill or task, physically-practiced errors must be committed and corrected in order to graduate to a zero-error level of skill, as per the characterisation of early-phase learning and the role of errors in driving this learning (Wolpert, Diedrichsen and Flanagan, 2011). It can then be justified, by extent of functional equivalence, that a similar volume of error commission-correction cycles must be observed during AO as are committed in PP to graduate in skill level to the same degree. In reality, the requisite volume of cycles in AO is likely greater than the volume of cycles in PP required to reach the same level of proficiency, given the evidence that independent PP lends itself to faster motor skill acquisition than independent AO (Cross et al., 2008). The improvements seen in the studies presented above could have been driven by basic exposure to and PP of the motor task alone, offering a brief increase in skill proficiency as participants formulated an internal model of the task. However, the volume may not have been sufficient to expose participants to enough AO-sourced sensory feedback to differentially develop their internal models. The additional volume included in the study by Weir (1988) and resultant significant difference in the two modelling effects makes a compelling case for this requisite volume concept. Limiting training volume could prevent participants from advancing to later stages of skill acquisition and learning, where a difference in skill proficiency related to model type might become more pronounced. When using AO as an independent motor learning strategy – i.e., not paired with PP – training volume should likely be at *least* as high as the physical training volume known to be needed to reach an intended level of motor skill proficiency. When combined with PP, total training volume can likely be reduced, due to the advantageous effect that this pairing has on motor learning outcomes.

2.6. Research question and hypotheses

Based on the justifications, theory, and mechanisms discussed above, we believe that there exists strong evidence that AO is best applied as a motor learning strategy when observers watch a learning model, who makes and corrects errors, instead of a skilled model, who makes no errors. Differences in the two modelling effects on motor skill proficiency are likely best demonstrated when participants use AO on a longer time scale, to provide a sufficient amount of sensory feedback and error commission-correction cycles to meaningfully improve the observer’s internal models of the motor skill. Furthermore, we believe that this effect will be amplified when learning model AO is paired with PP, giving the observer opportunities for processing of sensory feedback obtained during AO and online reiteration of their internal models during subsequent PP. Accordingly, the primary objective of the proposed work is to investigate the differential impact of observing a skilled model or learning model on motor skill acquisition when paired with PP in a long-term motor learning program. **We hypothesise that in a long-term training program, pairing learning model AO with PP will result in superior motor skill acquisition than pairing skilled model AO with PP.** This hypothesis will be tested by training study participants in a dart-throwing task using AO+PP as their motor learning strategy and assessing their skill acquisition using the mean radial error (MRE) of their throw (the mean distance of a series of dart throws from the bull’s eye). Dart throwing was identified as an appropriate motor task owing to a number of factors, including the simplicity with which performance can be quantified and scored (i.e., as distance from a target), the ease of representing the skill's kinematics to an observer using a sagittal-view recording, and the prefabricated dart-throwing infrastructure in the Laboratory for Brain Recovery and Function. Furthermore, previous studies have similarly investigated motor learning using dart-throwing as a model motor skill and have been successful in demonstrating significant changes in performance (Weir, 1988; Tyĉ and Boyadjian, 2011), implying that it is a skill amenable to learning and refinement in the paradigm of a research study.

The secondary objective of this work is to determine the differential impact of observing a skilled model or learning model on motor skill transferability – a shift in the parameters and goals of the task, while still engaging the same motor skill – when paired with PP in a long-term motor learning program. **We hypothesise that participants who complement long-term PP with AO involving a learning model will perform better on a modified motor task than participants whose AO involves a skilled model.** This hypothesis will be tested by assessing the MRE of participants' throws on a dart-throwing task with different criteria for success than the previously discussed dart-throwing task.

Chapter 3: Methodology

3.1 Participants

Forty-one prospective participants were invited to participate in the study through word-of-mouth and virtual information posters (see Appendix A). Participants' eligibility was assessed using a two-stage screening process, the first being online, and the second in-person. Previous work done by Tyĉ and Boyadjian (2011) utilising a training volume and duration similar to the one proposed by this study (see *3.3*, below) saw a statistically significant increase in dart-throwing performance in a single group of 6 participants, implying that a total sample size of N=12 may be appropriate to observe a significant change in performance over a 6-week time period. To determine the minimum sample necessary to observe a difference between two groups over the course of a 6-week time period, an *a priori* power analysis was conducted in G*Power 3.1.9.4 (see Appendix B for detailed protocol). This analysis indicated that a total sample size of N=24 would be appropriate to detect a significant difference between two equally-sized groups.

Participants were required to be aged 18 or older, with normal or corrected-to-normal vision, and to be in good health (i.e., with no self-reported neurological or mobility-impairing diseases, conditions, or illnesses, as disclosed using an online screening form). Participants' handedness was also assessed during the online screening stage, using the Edinburgh Handedness Inventory (Oldfield, 1971). Right-handed participants (a score of 40 or higher) were considered eligible, as the model the participants were to observe was right-handed, and it has been demonstrated that AO efficacy is sensitive to the model's handedness likeness to observers (Rohbanfard and Proteau, 2011). Participants were also required to be novice to the motor skill; namely, having little to no experience throwing darts, so as to ensure that there is ample opportunity for early-phase learning to occur. This was assessed using an email questionnaire asking questions about prospective participants' familiarity with dart throwing in general, the frequency of their participation in dart-throwing activities, and how long ago they last threw a dart (see Appendix C for questionnaire details). Participants who were found to be sufficiently unfamiliar with dart-throwing tasks and met all other inclusion criteria were asked to visit the Laboratory for Brain Recovery and Function for an introductory session to complete the second, in-person component of the screening process, a 15-throw pretest of the dart throwing task described in *3.3*, below. Participants' performances on the pretest were assessed, and participants with an MRE greater than or equal to 8.5cm were considered sufficiently novice at the dart-throwing task to participate in the study. Participants with an MRE less than 8.5cm were considered experienced at dart-throwing tasks and were excluded from further participation in the study. This cut-off threshold was based on prior work completed by the Laboratory for Brain Recovery and Function in which inexperienced individuals were recruited to learn a dart-throwing task: those individuals' mean dart-throwing scores at baseline were used to inform this estimate of "novice" dart-throwing ability. Of the 41 individuals recruited for participation, 24 met eligibility criteria and were invited to participate in the study.

3.2 Groups

The 24 eligible participants were pseudorandomised equally into one of two AO modelling conditions – skilled model or learning model (n=12 per condition). Given that participants were recruited on an ongoing basis over the course of the study's duration, participants were assigned to groups in one of two ways: when the number of participants in each group was equal, a participant was assigned randomly; when the number of participants in each group was unequal, the participant was assigned to the group with fewer participants. Both groups participated in AO of a model performing the dart-throwing task. To authentically represent both a learning and skilled model, the footage used for both groups' AO was produced by having a model novice to dart-throwing train their throw over the course of 9 weeks. In the earlier weeks of filming, kinematics and performance associated with novice performance were emphasised, while as the model's skill level advanced in later weeks, expert-associated kinematics and performance were emphasised. Kinematics were characterised based on studies by Tran, Yano, and Kondo (2016), Nakagawa et al. (2015), Obayashi et al. (2009), Schorer et al. (2012), and Tamei et al. (2011), which were collectively used to identify and differentiate the throw kinematics to be progressed to during different stages of the model's training (see Appendix D for further details).

The skilled model group observed footage of the model's performance only in the late weeks of the 9-week training program described above, once the model exhibited skilled performance in the dart-throwing task and executed it with perfect kinematics and resultant near-perfect performance outcomes (i.e., with ideal kinematics and a very low or absent MRE on the specified dart-throwing task). The performance level of the model was constant over the course of the participants' training program, meaning that each session attended by participants involved observing the same quality of skilled performance.

Conversely, the learning model group observed footage of the model that illustrated progression from unskilled to skilled performance over the course of the model's 9-week training program. During the initial stages of the participants' observation of the model, the footage showed the model committing numerous kinematic and performance errors (i.e., with poor form, returning large MREs) associated with novice performance. Over time, the participants observed a gradual correction and reduction in these errors, and eventual graduation to improved kinematics and performance outcomes. In the later stages of the participants' observation of the model, the learning model demonstrated advanced kinematics and performance associated with expert performance, resembling that of the footage observed by the skilled model group throughout their program. Both the learning model and skilled model group completed equal amounts of PP of the dart-throwing task following their respective AO observation, as described in detail in *3.3*, below.

3.3 Experimental task and protocol

See Figure 3 at the conclusion of this section for a visual timeline of study participation.

After obtaining written informed consent from each eligible participant during their first visit to the laboratory, participants were introduced to the dart-throwing task first described in *2.5*. The objective of the task, which was clearly outlined to participants at the beginning of each session they attended, was to throw a dart to attempt to hit the center of the board (the bull's eye). Following this explanation, participants were asked to complete the fifteen-throw pretest discussed in *3.1*. MRE was measured by using a transparent overlay sheet placed on top of the dart board, with reference markers used to identify the position of the sheet relative to the board and the origin coordinates of the bull's eye. Each time a dart struck the sheet overlying the board, the puncture left by the dart piercing the sheet was marked with a permanent marker. The distance of this puncture from the bull's eye was measured manually using a ruler, providing the MRE of each throw the participant completed.

Following the introductory session involving the 15-throw pretest and assessment of eligibility, follow-up sessions began with re-describing the goal of the dart-throwing task to ensure that it was clearly understood prior to beginning the session. The participant then completed five blocks of alternating AO and PP, first by observing footage of their group's respective model performing the motor task (Figure 1).

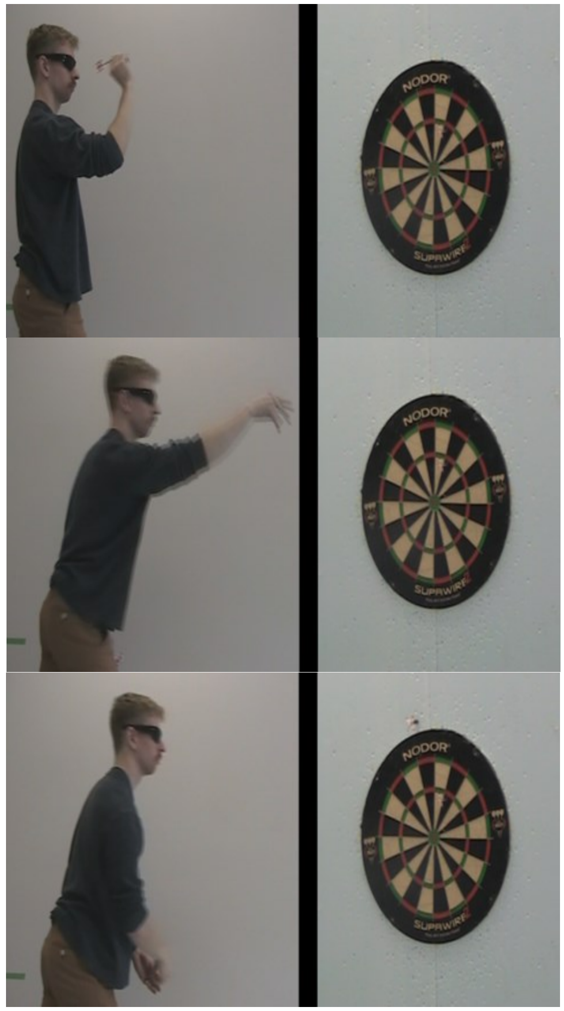

Figure 1: *Screen capture sample of AO footage to be shown to participants. In the uppermost panel, the model prepares for the throw. The middlemost panel shows the release of the dart. In the lowermost panel, the dart misses the board, indicating an unsuccessful task attempt.*

The monitor observed by participants was split into two halves, showing the model in a sagittal-plane view on the left-hand side, and the dartboard on the right-hand side. The participant observed the model preparing for the throw, drawing back, and then releasing the dart. The footage showed the dart being released, travelling across the room, and landing in the dartboard, with both halves of the monitor in sync with one another. This provided the participant knowledge of the model's results and a clear indication of whether the attempt at the task was successful, while simultaneously allowing them to observe the kinematics leading to the task result. However, participants received no external direction from the experimenter relating to which elements of the model's kinematics to pay attention to. Once 15 throws were observed, the video was paused, indicating that the observation block had concluded. The participant then physically performed the dart-throwing task themselves by completing a physical practice block of 15 throws. At the beginning of each physical practice block, a transparent overlay sheet marking the bull's eye position was placed over the dart board, similar to the 15-throw pre-test. As each dart struck the board, it punctured the sheet. After 15 throws were completed, the sheet was removed and replaced with a new sheet indicating only the bull's eye position, and the punctured sheet was highlighted with a permanent marker. Similar to the observation blocks, the experimenter did not provide the participant with any feedback on their dart-throwing kinematics or how these kinematic strategies related to the result they achieved on the task. Following completion of the sheet transfer, the footage of the model was resumed for observation of another fifteen throws, followed by physical practice of another fifteen throws, until a total of five AO+PP blocks had been completed (with 75 throws having been observed, and 75 throws having been physically practiced). The MREs from each throw on the highlighted overlay sheets were measured manually using a ruler and recorded following the end of the session.

Participants completed 18 sessions over the course of the study, inclusive of the introductory session. At a rate of 3 sessions per week, participation in the study from recruitment to completion took approximately 6 weeks for each participant. Over the course of the study, each participant would observe and physically throw over 1,200 darts. This specific training volume was established based on the discussion in section *2.4*, which encouraged the use of an AO+PP volume known to elicit improvements in similar dart-throwing tasks when trained using

PP alone. Tyĉ and Boyadjian (2011) found that participants who trained a dart-throwing task over 6 weeks with 2-3 sessions per week each consisting of 60-80 throws – accumulating more than 1,200 throws over the course of the study – saw a 34% increase in throwing accuracy post-training. This program was considered a prospective benchmark for establishing a sufficiently high PP volume, both in duration and number of throws, to see improvements in this study's dart-throwing task.

During the participant's final visit (session 18), the session began by describing a modified goal for the dart-throwing task. The goal of the transfer task was to hit a target in the boundaries of the concentric ring most proximal to the bull's eye. At the beginning of each practice block, a new target within the boundaries of this ring was illustrated to participants (Figure 2), requiring participants to hit five separate targets over the course of the session. This modified task was designed with the proposed study's secondary hypothesis in mind; namely, to identify differences in motor skill transferability by testing the dart throw on a different task. The participant observed their respective model completing the original dart-throwing task, and then performed 75 throws of the modified task. Mean radial error was measured in the same way as the original task (i.e., manually, with a ruler), but using the block-specific targets as origin coordinates. Each block's target was consistent across participants and between groups. Following this session, participation in the study was completed, and all participants received a debriefing form (see Appendix E).

Figure 2: *Targets for the modified dart-throwing task, indicated by yellow X's.*

In addition to collecting participants' performance data by recording their scores on both dart-throwing tasks, participants' kinematic data was also collected. This was accomplished by recording sagittal-view video footage of each participant as they trained the dart-throwing task during their physical practice blocks. While use of this video footage beyond its collection or subsequent kinematic analysis was not within the scope of this study, its collection may be of use for future studies investigating the development of dart-throwing kinematics over the course of early-phase motor learning, particularly in response to alternative motor learning strategies such as AO.

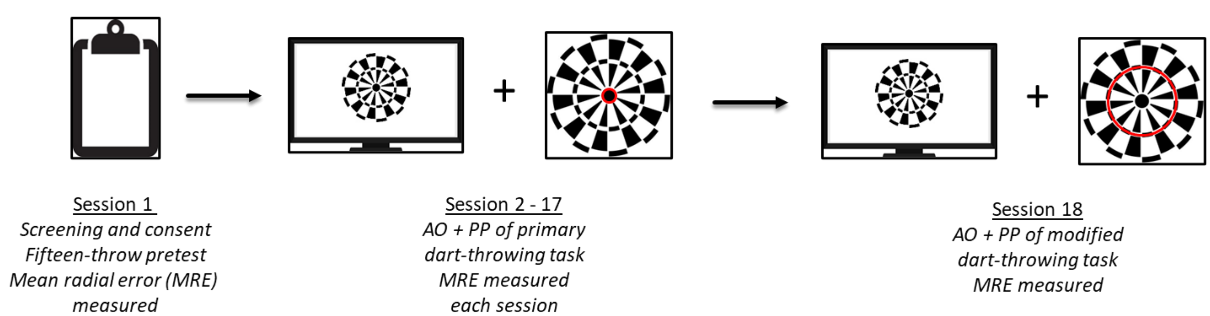

Figure 3: *Conceptual figure showing timeline of study participation, progression, and points of measurement.*

3.4 Statistical analysis

The questions posed in the hypotheses were addressed using two statistical tests conducted in RStudio (RStudio Team, 2022). To address the study's primary objective – namely, determining whether observing a learning model leads to superior motor learning outcomes than observing a skilled model – a linear mixed effects (LME) model, implemented in RStudio using lme4 (version 1.3.1), was used to assess factors impacting MRE between groups and over time. The independent variables were **group** (with levels *skilled model* and *learning model*), **session** (with levels *2-17*, corresponding to the sessions on which the primary task was attempted), and **block** (with levels *1-5*, corresponding to the five blocks completed per session), all which were incorporated into the model as fixed effects. A hierarchal random effect term was used to nest the effect of block within session within participant. The fixed effects for block and session were centered on zero and scaled from -1:1, and score was converted to transformed zero-mean and unit variance. Significant effects (alpha=0.05) in the model were examined by plotting the predicted effects of the model, and effect sizes were estimated using partial r^2 values. To address the secondary objective – the question of skill transferability as indicated by each groups' performance on the modified dart-throwing task – an independent t-test was conducted in IBM SPSS Version 27 (IBM Corporation, 2022). This t-test was conducted at the 95% confidence level comparing between-group session 18 MREs (n=12 per group), with the effect size estimated using Cohen's *d*.

Chapter 4: Results

4.1 Participant demographics and study timeline

Participants' demographic data is summarized in Table 1 below. Inclusive of the introductory session, eligible participants completed 3 sessions per week (mean = 2.79, range 2.2-3.6), over the course of approximately 6 weeks (mean = 6.17 weeks, range 4.71-7.71). In general, sessions were separated by no more than 1 calendar day, to allow time for offline consolidation of learning, and no less than 7 calendar days, to prevent a loss of familiarity with the task. However, owing to the ongoing COVID-19 pandemic and related public health measures, there were instances wherein one participant had to complete 3 sessions on 3 consecutive calendar days and another participant completed their 18th session more than 7 days after their 17th.

Table 1: *Demographic data for study participants.*

Group	Mean age (years)	Gender presentation (n)
Learning	23.8	Female (10), Male (2)
Skilled	22.8	Female (10), Male (2)
Overall	22.9	Female (20), Male (4)

4.2 Effect of modelling condition on motor skill acquisition

Upon completion of the study, participants' data were collated into group means for sessions 2-17, as summarized in Table 2 and visualized in Figure 4. LME analysis revealed several findings from the dataset, with the omnibus test results summarized in Table 3. There was a significant improvement in participants' dart-throwing ability over the course of the study independent of which group they were in, as indicated by a significant effect of **session** on **MRE** ($p<0.001$). It was also found that there was a significant effect of **block** on **MRE**, indicating that lower MREs were generally associated with later blocks of any given session ($p<0.001$). While the learning model group generally tended to demonstrate lower MREs than the skilled model group across all sessions, analysis did not indicate a significant effect of **group** on **MRE** ($p = 0.453$). Furthermore, all interaction terms were nonsignificant ($p>0.05$), with the exception of **session*block** on **MRE**¸ indicating that the block-dependent effect on performance varied as participants progressed into later sessions of the study ($p=0.008$). Specifically, during the earlier phases of the study, there was a greater-magnitude difference in MRE between blocks 1 and 5 of any given session, as well as larger, positive MRE differences between blocks 5 and 1 of consecutive sessions. However, as sessions progressed, these differences became smaller, resulting in less variable MREs across all five session blocks.

***Table 2**: Session-wise descriptive statistics for both the learning model group (LMG) and skilled model group (SMG) for sessions 2-17. Mean radial error (MRE) is reported in cm, representing absolute error as measured from the bull's eye target. Standard deviations are listed in parentheses adjacent to each sessional MRE. Ranges are reported in cm, with the two values indicating the minimum and maximum MRE for each group at each session.*

Session	***LMG MRE (SD)***	***SMG MRE (SD)***	***LMG Range***	***SMG Range***
2	9.68 (1.82)	10.41 (1.94)	6.80, 12.88	7.74, 12.96
3	9.37 (2.34)	10.06 (2.24)	6.29, 14.26	6.15, 12.62
4	9.28 (2.23)	9.87 (2.54)	6.36, 14.71	5.71, 13.41
5	9.31 (2.28)	9.45 (2.14)	6.09, 14.27	6.76, 12.64
6	8.40 (1.48)	9.97 (2.13)	6.18, 10.88	6.92, 12.98
7	8.53 (1.82)	9.28 (2.32)	5.52, 11.56	6.04, 13.37
8	8.41 (2.10)	9.16 (2.63)	5.79, 12.51	5.74, 12.96
9	8.44 (2.21)	8.89 (2.20)	6.30, 12.89	5.14, 12.20
10	8.17 (1.73)	9.06 (1.87)	6.39, 11.91	5.57, 11.61
11	8.28 (1.88)	8.50 (2.03)	6.55, 12.40	5.04, 11.63
12	7.79 (1.75)	8.73 (2.26)	5.92, 11.20	4.96, 11.51
13	7.54 (1.52)	8.46 (2.08)	5.90, 11.10	5.94, 12.58
14	7.64 (1.83)	8.86 (2.12)	5.38, 12.21	5.55, 12.30
15	7.94 (2.00)	8.93 (2.10)	5.97, 12.75	4.74, 12.39
16	7.90 (2.51)	8.49 (1.89)	5.81, 15.12	5.25, 11.00
17	7.60 (1.80)	8.25 (1.65)	5.21, 11.58	5.55, 10.50

***Table 3:** Linear mixed effects omnibus test findings, zero-mean centered.*

Model parameter	***Coefficient***	***Standard error***	***Confidence interval (95%)***	***T-statistic (26422)***	***P-value***	***Partial r^2***
Intercept	-0.06	0.11	-0.28, 0.16	-0.56	0.575	-0.112
Group	0.11	0.15	-0.18, 0.41	0.75	0.453	0.151
Session	-0.19	0.02	-0.22, -0.15	-9.20	<0.001	-0.439
Block	-0.06	0.01	-0.08, -0.03	-4.63	<0.001	-0.117
Group * Session	2.82^{-3}	0.03	-0.05, 0.06	0.09	0.931	0.002
Group * Block	0.01	0.02	-0.02, 0.04	0.61	0.542	0.011
Session * Block	0.06	0.02	0.01, 0.10	2.67	0.008	0.065
Group * Block * Session	-0.03	0.03	-0.08, 0.03	-0.97	0.333	-0.021

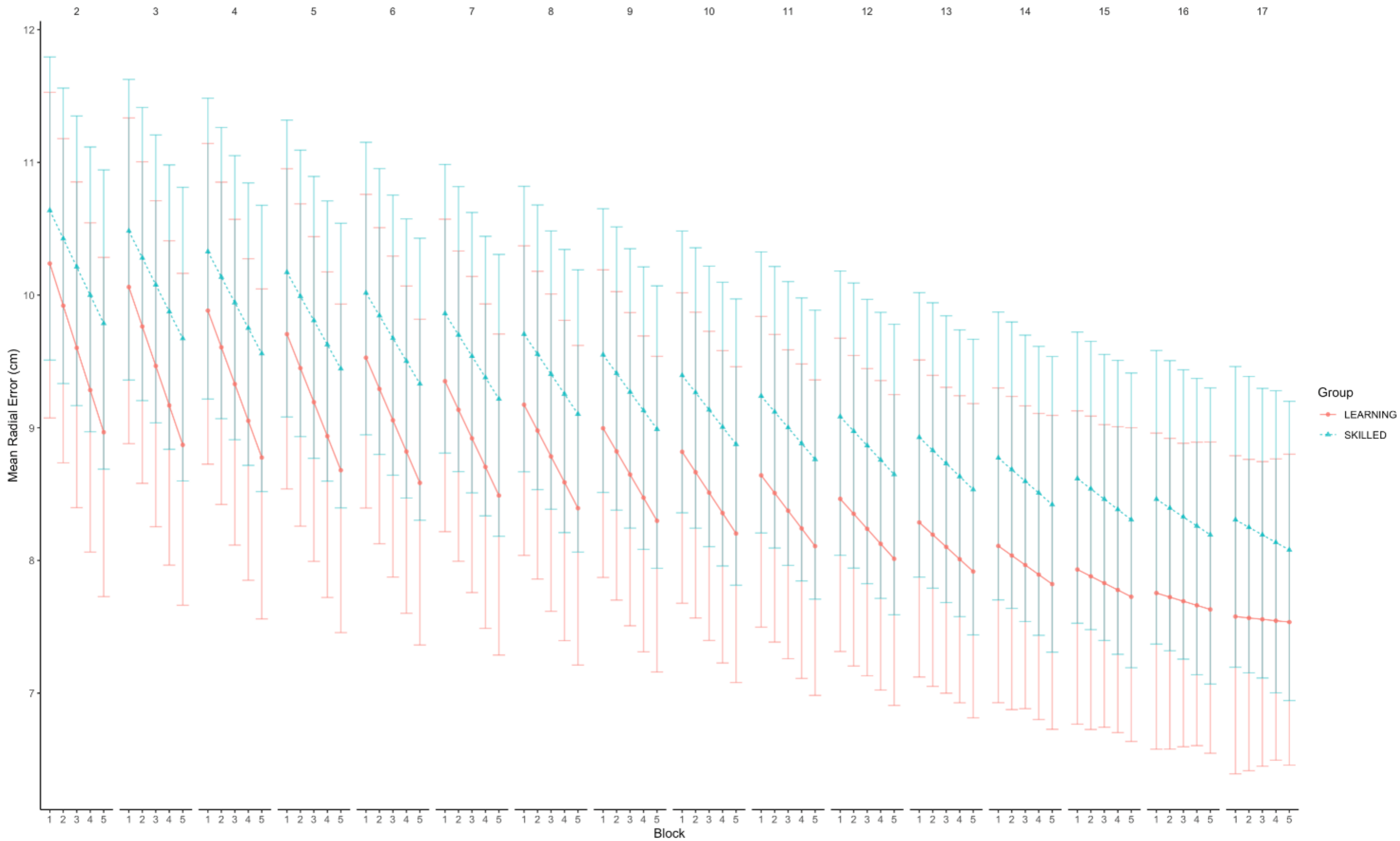

Figure 4: *Visualization of results from sessions 2-17, with separate curves displaying learning model group and skilled model group findings.* *Data is zero-mean centered and modelled to fit LME estimates. Blocks are indicated by separate points and are linked within-session. Error bars represent bootstrapped 95% confidence intervals based on each group's respective sessional means.*

4.3 Effect of modelling condition on motor skill transferability

The pooled session 18 MREs are summarized in Table 4. Similar to the primary dart-throwing task, the learning model group demonstrated less error overall on the modified dart-throwing task, as evidenced by a lower pooled MRE; however, the independent t-test did not indicate that this difference was significant ($t(22)$, $p = 0.361$, Cohen's $d = 0.38$) (Figure 5).

Table 4: *Session 18 descriptive statistics for the learning model group (LMG) and skilled model group (SMG).*

Group	**LMG**	**SMG**
MRE (cm)	7.64	8.43
Standard deviation (cm)	2.23	1.95
Range (cm)	5.55, 11.29	4.69, 10.81

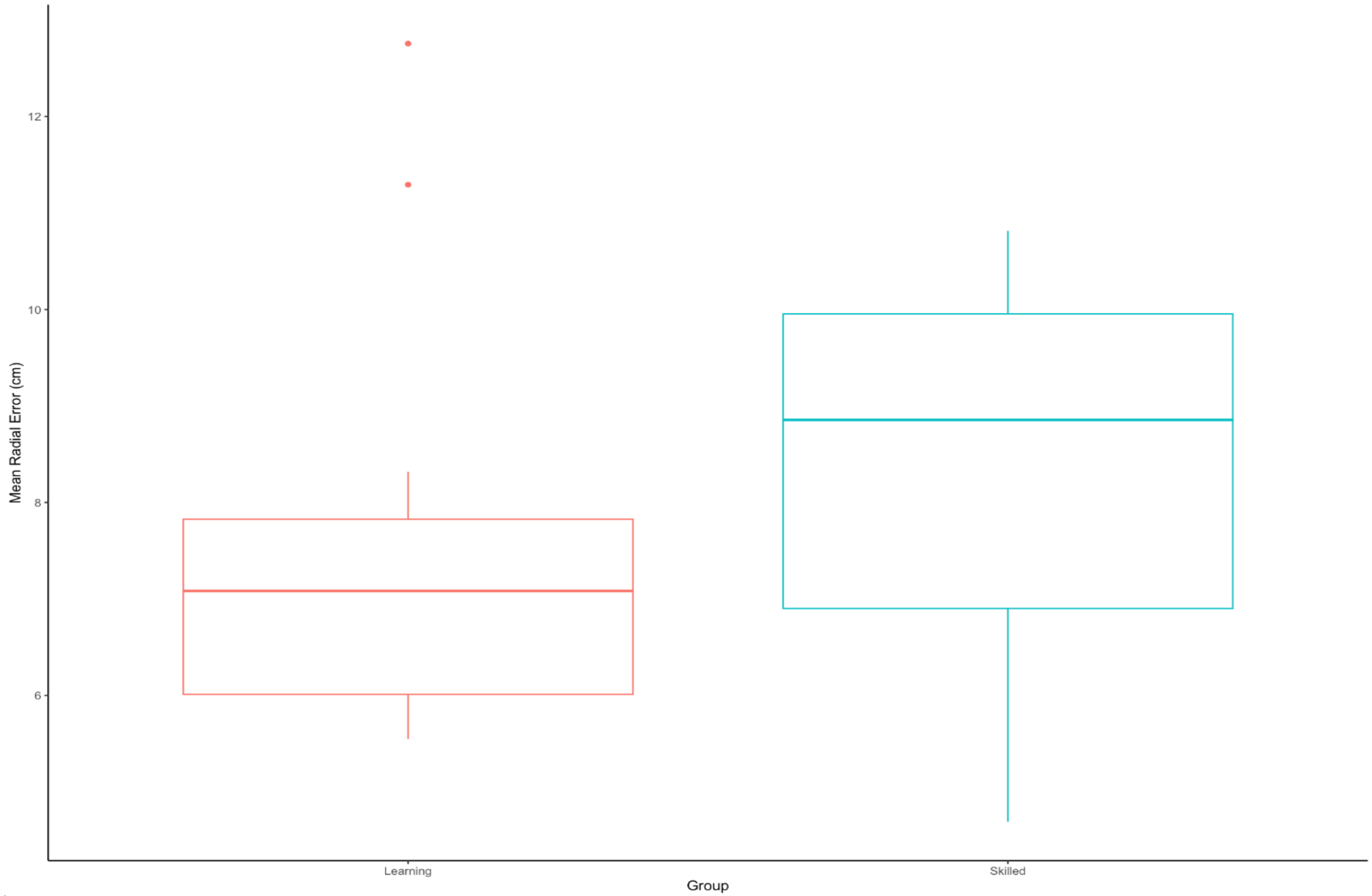

Figure 5: *Visualization of results from session 18. Separate boxes display the learning model group and skilled model group findings. Group medians are indicated by the solid horizontal line transecting the box, 1st and 3rd quartiles by the boundaries of the box, ranges by the span of the vertical lines emerging from the box, and outliers by any points not contained within the box.*

Chapter 5: Discussion

5.1 Overview of findings

This study aimed to evaluate the effect of pairing PP with AO of a learning model on longitudinal motor learning outcomes in comparison to a conventional skilled model. This was accomplished by teaching inexperienced participants how to perform a dart-throwing task over the course of a 6-week training program coupling PP and model-specific AO. Participants' ability to transfer and generalize the dart-throwing skill to different task environments was evaluated using a modified dart-throwing task completed at the end of the 6-week timeline. The primary hypothesis of this study was that observation of a learning model, who commits and corrects errors over time, would lead to superior motor learning outcomes as compared to observation of a skilled model. Furthermore, it was also hypothesised that learning model AO would lead to superior motor skill transferability compared to skilled model AO, as evidenced by performance on a modified dart-throwing task.

Over the course of the study, participants' performance on the primary dart throwing task improved significantly as a function of session; namely, their exposure to coupled PP+AO appeared to drive acquisition of dart-throwing ability. This result is consistent with motor learning theory relating AO and PP exposure to skill acquisition, although it is challenging to discern exactly how much of this acquisition was owed to the AO material versus the physical exposure to the dart-throwing task. Nevertheless, significant learning occurred in response to the practice completed over the course of the study, independent of which model participants observed. Furthermore, there appeared to be a block-dependent effect on participants' MRE, wherein participants showed lower MREs in later blocks of each session. This effect began to diminish over the course of the study, which can likely be attributed to participants' ongoing consolidation of feedback and retention of the parameters of the motor skill. This observation is consistent with previous findings in the literature, which describe the effect of **offline learning**: namely, gains in skill performance are consolidated not only by practice within a session, but stabilization and enhancement that occurs between sessions (Censor, Sagi, and Cohen, 2012). While this effect is not as pronounced as the improvements that occur during online (i.e., within-session) learning, it still plays a significant role in skill advancement during early-phase learning and is heavily influenced by practice schedule and between-session sleep (Censor, Sagi, and Cohen, 2012). It is apparent that offline learning began to play a more significant role during later sessions of the study, as evidenced by a diminishing difference in late-session and early-session MREs, and even became negative in the case of Session 16, Block 5, and Session 17, Block 1 for the learning model group (as shown in Figure 4).

With respect to these findings concerning online and offline learning of the primary dart-throwing task, it is significant to note that the participants selected to participate were *novice* to dart-throwing tasks in general. This status was evaluated using both subjective and objective measures (i.e., the screening questionnaire and performance on the fifteen-throw pretest, respectively) and was integrated into the study design so as best to capture the effects of AO+PP and error-based learning, both of which were predicted to be most prominent in early-phase learners. Individuals who exhibited a higher skill level at dart throwing during either of these screening points were excluded from participating. In this sense, there is a certain degree of selection bias in this study's participant population, which raises the question as to whether participants' significant improvements in dart-throwing skill were due to the effectiveness of the training program, or simply due to their inexperience with dart throwing and a high likelihood that they would improve in skill regardless of the training program they followed. In any case, it is challenging to generalize these findings to a broader population of individuals, particularly those who may already have experience with dart-throwing tasks and therefore less room for improvement before reaching a skill plateau.

While the learning model group tended to commit less error overall on both the primary and modified motor tasks as compared to the skilled model group, these differences were not significant at the 95% confidence level, characterised by large standard deviations within groups and a relatively small partial r^2 values (Table 3). Unsurprisingly, this finding was also accompanied by nonsignificant interaction effects of group*time and group*block. Given this outcome, **both the primary and secondary alternative hypotheses of this study are rejected**: at this time, the data acquired in this study do not suggest that when coupled with long-term PP, AO of a learning model leads to improved motor skill acquisition and transferability as compared to AO of a skilled model.

5.2 Factors contributing to findings and considerations for future work

Although this result is not consistent with the robust body of literature and theoretical predictions in support of a learning model AO protocol, there are a number of contextual factors to consider. As mentioned in *5.1*, there are challenges associated with discerning how much learning occurred due to PP, and how much occurred due to AO exposure. This study used a 1:1 ratio of AO:PP, meaning that for every observed throw, participants also physically completed one throw. This is generally consistent with the designs used in prior work, including McCullagh and Meyer (1997) and Pollock and Lee (1992) wherein both studies used 1:1 AO:PP ratios and found that while observing a model led to better motor learning outcomes compared to PP-only control groups, there was no significant difference between models. Interestingly, Weir (1988) used a ratio of 8 AO dart throws and 60 PP dart throws and found no significant differences between the study's AO groups and PP-only control groups, including the control group that completed 68 PP throws to account for differences in exposure volume. Work completed by Kraeutner (2019) examined the effect of motor imagery (MI) and PP on performance of a dart-throwing task over the course of 10 days, using a volume of 90 throws per session. Participants completed these throws in one of three group conditions: 1) MI for days 1-5, and PP for days 6-10, 2) PP for days 1-5, and MI for days 6-10, or 3) PP for days 1-10. Of these conditions, the PP group showed the largest changes in dart-throwing performance between days 1 and 10. In the motor simulation model proposed by McNeill et al. (2019), MI+PP shows a greater benefit with respect to early learning outcomes compared to independent PP, though not as great as AO+PP. This is to say that the findings from Kraeutner (2019) indicate results similar to those found in prior literature: namely, that motor learning outcomes acquired using alternative learning strategies coupled with an equal or greater dose of PP result in either nonsignificant differences between alternative strategy derivatives (e.g., different AO models) or between PP-only groups.

When reflecting on findings from Cross et al. (2008) that on an independent basis, PP is generally a preferable motor learning strategy to AO, it is conceivable that the 1:1 coupling ratio used in this study and others resulted in a "washout" effect, wherein the majority of dart-throwing skill acquisition was driven by PP and minorly by AO. Namely, participants may have improved their ability to throw darts simply because they threw a multitude of darts over the course of the study, and the overwhelming stimulus of this physical practice diminished the perceptibility of any effect from the accompanying AO that participants completed.

One approach to addressing this effect would be through the introduction of a control group into the study design: in particular, a group completing only PP of the dart-throwing tasks, as well as a group completing only AO of the dart-throwing task with scheduled physical tests of their dart-throwing ability. When contrasted with the results of the groups included in this study, the learning outcomes of these groups would describe the magnitude of the effect that coupled AO and PP had compared to their independent counterparts. While this design would have elucidated the findings of this study, it was opted against for two key reasons. Firstly, without the hindsight of this work's results in mind, the purpose of introducing these control groups *a priori* would have been limited to determining the general differential effect of combined AO and PP on independent AO and independent PP, which has been already established, particularly in early-stage learners (McNeill et al., 2019). Moreover, there were concerns at the outset of the study amongst the authors surrounding the feasibility of recruiting and retaining 24 participants over the course of the 6-week study period, which would have been more challenging with 36 or even 48 participants to suitably populate control groups.

Another factor that may have influenced the results of this work was the participants' lack of vicarious knowledge of performance surrounding the dart-throwing task. This can be thought of as externally-provided feedback that illustrates certain elements of performance that may be beneficial to the learner, either with respect to the learner's own performance, or with respect to the model's performance in the case of AO. Findings by McCullagh and Meyer (1996) indicated that individuals in receipt of feedback on their own performance achieved better motor learning outcomes compared to those who did not receive feedback, independent of the type of model they observed. However, in the case of the present study, participants received no feedback or cues when observing their respective model performing the dart-throwing task and subsequently physically practicing it themselves. While the intent of this design was to reduce any interference with the effect of the AO participants completed, eliminating this opportunity for external feedback could have affected participants' interpretation of their own performance strategies as well as their interpretation of their observed model's kinematics. As per Schmidt's schema theory, a key determinant of trial-by-trial error correction is an individual's knowledge of results, enabling them to combine sensorimotor evaluations of task-relevant effectors with their objective and subjective interpretations about the task outcome to improve future iterations of a motor plan (Diedrichsen et al., 2010). Participants in the present study *did* receive knowledge of their results based on their understanding of the task objective and how close their dart was to the target, but it is conceivable that more substantial feedback from the experimenter regarding their strategies to obtain such a result could have positively influenced subsequent task attempts. This may have been particularly advantageous for the learning model group, where external feedback specific to the model's performance could have highlighted particular errors and corrections that the model made and provided participants with explicit insight regarding their own kinematic strategies to complete the task. This hypothesis is particularly relevant given indications in prior literature that error recognition is not only conserved during action observation but has been demonstrated to effectively drive learning as well (Burke et al., 2010; Wolpert, Diedrichsen, and Flanagan, 2011). Compared to AO feedback in the skilled model group – which would have been devoid of any instructions surrounding erroneous kinematics, given the nature of the model's performance – AO feedback in the learning model group could have provided participants with a promising edge to fully appreciate the nuances of their model's performance and use it to advance their own motor learning.

It is of interest to note that although the differences in primary and modified motor task performance between groups were not significant, visual inspection of the raw data revealed relatively larger decreases in MRE for the learning model group during the earliest phases of the study (i.e., up to session 7) that were not as readily apparent in the skilled model group. While the curve slopes describing the groups' changes in MRE began to resemble one another more closely after this point, this feature of the data carries potential implications for the learning trajectories of each group. When considered in the context of the cognitive stage of learning and its dependence on error commission and correction, it is conceivable that these large swings in MRE reflected the "earliest" of this early-phase motor learning process in the learning model group. This could have involved participants in this group aggregating and processing error-correction information from the model and coupling that with their own practice of the task, resulting in a rapid improvement from baseline that was not similarly observed in the skilled model group. A retrospective analysis was conducted using the same LME approach as specified in *3.4*, with the **session** variable constrained to sessions 2-7. This secondary analysis indicated no significant effect of **group** on **MRE**; namely, any early performance changes were not found to be significantly different between groups based on the model's estimates (p=0.298, partial r^2=0.171). Therefore, it is more likely that the large score deviations witnessed in these early sessions captured the variation often exhibited in early-stage learning, as characterised by participants' tendency to explore new kinematic strategies and discover various errors and successes in a novel motor task. Nevertheless, if combined with the alterations to this study design proposed above, further examination of this particular episode of the motor learning continuum has the potential to answer several interesting questions relating to the duration of the earliest phase of cognitive learning and its receptiveness to different forms and doses of AO.

Chapter 6: Conclusion

Motor learning is a complex process driven by a myriad of factors and is heavily influenced by time, prior skill level, and task-relevant interpretations. While AO has been shown to be a potent driver of motor skill acquisition, and the application of learning-model AO is supported by promising evidence and conceptual predictions, the data from this study do not explicitly support any sort of advantage compared to conventional AO of a skilled model. Nevertheless, this work must be viewed as a first step in exploring the efficacy of learning-model AO over a long-term timeframe, which is in and of itself a novel investigation relative to previous work. Future work is needed to understand the specifics of this effect, or lack thereof, especially considering the inclusion of parameters such as modified AO:PP dosing and vicarious knowledge of performance embedded in study designs. It may also be of interest to explore specific applications of a learning model, such as in the context of stroke rehabilitation using a model that represents a patient’s specific Chedoke McMaster staging (Gowland et al., 1993), or in return-to-sport settings using a model of a similar skill level to a recovering athlete. Beyond clinical implications, however, this work offers intellectual contributions to the fields of neuroscience, behavioural psychological, and motor control, advancements in which promise a wide range of benefits. Expanding our collective understanding of the principles and mechanisms driving motor learning can assist in optimizing and accelerating motor learning programs and environments, leading to new avenues of thought and application relating to motor skill acquisition and development.

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Appendices

Appendix A – Virtual information poster used for recruitment purposes

LABORATORY FOR
BRAIN RECOVERY AND FUNCTION
SCHOOL OF PHYSIOTHERAPY
DALHOUSIE UNIVERSITY

Call for volunteers!

We are recruiting novice dart-throwers for a study examining how different types of action observation (AO) impact motor skill performance outcomes.

The overall aim of this study is to **illustrate whether observing a learning model or a skilled model in AO leads to better performance on a dart-throwing task.**

You will be asked to visit the Laboratory for Brain Recovery and Function at Dalhousie University for a total of 18 sessions, each lasting no longer than 30 minutes, spread across 6 weeks (3 sessions per week). You will be compensated $135 for your time.

Following an introductory session for screening, consent, and familiarization with the task, each session will involve watching a video of someone throwing darts, followed by a period for you to physically train the dart-throwing task yourself.

To be eligible to volunteer, you must be 18 years of age or older, right-handed, have normal or corrected-to-normal vision, and have no pre-existing neurological injuries or mobility impairments that would affect your ability to learn a dart-throwing task. You must also have little to no experience with dart throwing games or tasks in general.

Who to Contact: David Bowman, graduate student (MSc Rehab. Research, MSc Physiotherapy)
Email: aomodelstudy@gmail.com
Where: Rm 428 Forrest Building, Dalhousie University
Principal Investigator: Dr. Shaun Boe

Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**	Dart-throwing AO study **aomodelstudy@gmail.com**

Appendix B – *A priori* power analysis protocol

The following parameters were used to define the *a priori* power calculation completed in G*Power 3.1.9.4. It should be noted that it was initially intended to use a repeated-measures ANOVA to analyze the findings of this study, using four sessions as key measurement points. However, after concluding data collection, it was decided to analyze findings using a linear mixed effects analysis, as described in Chapter 3: Methodology. Therefore, the *a priori* power calculation protocol specified below reflects the initial sample size calculation and rationale for an N=24 sample size, which was maintained despite the change in analysis approach.

F tests - ANOVA: Repeated measures, within-between interaction

Analysis: A priori: Compute required sample size

Input: Effect size f = 0.246

α err prob = 0.05

Power (1-β err prob) = .80

Number of groups = 2

Number of measurements = 4

Corr. among rep measures = 0.5

Non-sphericity correction ε = 1

Output: Non-centrality parameter λ = 11.6190720

Critical F = 2.7437108

Numerator df = 3.0000000

Denominator df = 66.0000000

Total sample size = 24

Actual power = 0.8018783

Appendix C – Screening Questionnaire

The following material is an adaptation of the screening questionnaire sent to participants to determine their eligibility for the study. Any responses indicating that the eligibility criteria described in *3.1* were not met resulted in notifying the individual that they were not eligible to participate.

LABORATORY FOR
BRAIN RECOVERY AND FUNCTION
SCHOOL OF PHYSIOTHERAPY
DALHOUSIE UNIVERSITY
Inspiring Minds

LEARNING-MODEL ACTION OBSERVATION QUESTIONNAIRE

Below is a questionnaire used to determine whether potential participants are suitable for participation in studies involving action observation as a motor learning strategy. Please complete the questions honestly and to the best of your knowledge. All information, including your identity and contact information, will be kept completely confidential.
If you have questions regarding the study or the form below, please contact **aomodelstudy@gmail.com**.

The questionnaire includes 7 questions. Please answer the questions using the fillable fields below.

1. How old are you?

2. Do you have normal or corrected-to-normal vision (i.e. wear glasses or contacts)?

   Yes

   No

3. Do you have a history of any injuries or conditions (neurological, physical, or otherwise) that would, to the best of your knowledge, impact your ability to perform a novel dart-throwing task?

   Yes

      If so, please indicate:

   No

4. Please indicate your preferences in the use of hands in the following activities by indicating a check in the appropriate column. Where the preference is so strong that you would never try to use the other hand, unless absolutely forced to, put 2 checks. If in any case you are really indifferent, indicate a check in both columns.

Some of the activities listed below require the use of both hands. In these cases, the part of the task, or object, for which hand preference is wanted is indicated in parentheses.

Please try and answer all of the questions, and only leave a blank if you have no experience at all with the object or task.

Task	Left	Right
1. Writing	☐ ☐	☐ ☐
2. Drawing	☐ ☐	☐ ☐
3. Throwing	☐ ☐	☐ ☐
4. Scissors	☐ ☐	☐ ☐
5. Toothbrush	☐ ☐	☐ ☐
6. Knife (without fork)	☐ ☐	☐ ☐
7. Spoon	☐ ☐	☐ ☐
8. Broom (upper hand)	☐ ☐	☐ ☐
9. Striking Match (match)	☐ ☐	☐ ☐
10. Opening box (lid)	☐ ☐	☐ ☐
TOTAL (count checks in both columns)	☐	☐

5. Have you ever participated in a dart-throwing task for any of the purposes indicated below:

Yes, competitively.

Yes, recreationally, on a regular basis.

Yes, recreationally, on a semi-regular basis.

Yes, recreationally, on rare occasions.

Yes, but on a very limited basis (i.e. I have thrown a dart a few times in my life).

I have never thrown a dart in my life.

Other: please indicate:

6. If you answered “Yes” to Question 5, when was the last time you participated in a dart-throwing activity?

   Less than a week ago.

   More than a week ago, but less than a month ago.

   More than a month ago, but less than three months ago.

   More than three months ago, but less than six months ago.

   More than six months ago, but less than a year ago.

   More than a year ago.

   Other: please indicate:

7. During your dart-throwing task participation indicated in your response to Question 5, which of the following statements best describes your approximate frequency of participation (i.e. how often did you throw darts)?

   On a daily basis.

   More than once per week.

   Once per week.

   A few times per month.

   Once per month.

   A few times per year.

   Once a year.

   Other: please indicate:

Appendix D – AO model training program and timeline

In order to conserve the authenticity of the learning model and skilled model conditions to be used as AO material for participants, the model followed a 9-week training program to improve their dart throw by training the primary dart-throwing task discussed in this proposed study (i.e., to hit the bull's eye on the board). The model trained 2-3 times weekly, throwing between 60 and 80 darts per session. Each session was filmed from both a sidelong sagittal view, capturing the model's throw kinematics, along with a view of the dartboard, capturing the results of the model's throw. The specific material of this training program was produced by first examining literature that identified kinematics associated with both novice and expert dart throwers. Tran, Yano, and Kondo (2016) found that experts exhibited considerably less elbow displacement in the vertical plane than novices did, along with a tendency to keep their throwing limb perfectly aligned with the plane of their throw with little to no lateral tendency. Studies by Tamei, Obayashi, and Shibata (2011) and Obayashi et al. (2009) indicated that shoulder variance is significantly reduced in experts as compared to novices, while the 2011 study also found that experts tend to exhibit more trunk control and elbow stability than novices. Throw precision was found to be increased by reducing variation in joints, particularly those closest to the finger (Nakagawa et al., 2015). These kinematic characteristics were used to provide various objectives and assessment points to graduate towards advanced or "skilled" model status, while still demonstrating characteristics representative of a "learning" model along the training curve. The training program was subdivided into three blocks, each lasting three weeks each – novice, intermediate, and advanced.

During the novice block, the model focused on aligning their stance, reducing the degree to which their body lunged into the throw, and establishing comfortable shoulder and elbow positions. While joint variability was not entirely eliminated, particularly in the elbow and shoulder, the model's adjustments were largely focused on stabilising the body in space and controlling their center of mass during each throw, consistent with the directives from the literature discussed. In the intermediate block, the focus shifted to reducing variability in the shoulder and elbow and eliminating movement in the torso and hips (i.e., reducing any sort of lean *into* the dart throw). Small adjustments to elbow elevation were made – by lowering the elbow, the dart tended lower, while raising the elbow caused the dart to tend higher. The model's training log from this block indicated a growing ability to consciously make shifts in their throw kinematics to hit the bull's eye. This ultimately resulted in a re-introduction of a slight lean into the throw, as well as manipulations in joint elevation to achieve the intended outcome. In the advanced block, the model had established a dependent shoulder and elbow position, with limited or entirely absent trunk movement, and a consistent, deliberate lean during the release of their throw. Wrist and finger variability was reduced. It was also found that by slightly angling the dart tip upwards, accurate throw outcomes became more consistent. At the conclusion of this block, the model was able to consistently achieve accurate throws and hit the bull's eye, indicating a successful training program and adherence to the learning-to-skilled model learning curve.

Appendix E – Debriefing Form

The form below was sent to participants after their participation in the study had concluded.

Learning-Model Action Observation: Debriefing Form

One area of focus in our laboratory relates to examining different modalities for motor learning, including action observation, the observation of another individual performing a motor task or skill. Action observation can be an effective motor learning strategy because, just like physical practice, this technique activates the sensorimotor network and areas of the brain responsible for executing the motor task or skill we are observing. Recent research has indicated improved learning outcomes when using action observation concurrently with physical practice.

We are still seeking to answer questions regarding these improved learning outcomes, particularly in early-phase learners for whom pairing action observation and physical practice has been shown to be the most effective. This study has sought to understand how to best use action observation as a learning strategy for a motor skill being developed over a longer period of time spanning multiple weeks. By enmeshing the commission and correction of errors into the material that early-phase learners observe, we have hypothesized that this will promote better learning outcomes than observing material that demonstrates errorless performance of the motor task of interest. Your participation in this study has contributed to our efforts to understand how action observation works, and how to utilize it best in various learning environments. We greatly appreciate your time, energy, and efforts in participating in this study, and thank you for doing so.