UNIVERSITY OF TWENTE.

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How Real-World Objects Affect the Motor Skill Learning in VR

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M.Sc. Thesis
May 2024

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Abstract

This thesis explores the impact of controller fidelity in virtual reality (VR) on motor learning using a golf putting task among novice golfers. Participants were divided into three groups: those training with actual golf putter (Club), those using standard VR controllers (Con), and those equipped with real club incorporated VR controllers incorporating (ConClub). The study measured performance through initial release angle and ball travel distance across pre-tests, post-tests, and retention tests, alongside kinematic analysis focusing on sternal rotation.

Study does not find possible effects of real-world object interventions on motor learning in VR environments: no significant differences in performance were found between groups. Notably, the ConClub group showed reduced variability in performance on the skill retention test, suggesting that realistic haptic feedback may improve long-term skill retention. However, their movement patterns were located between the Club and Con groups, suggesting that while VR training combined with realistic putting does not exactly replicate real-world movements, a higher degree of movement reproduction can be achieved compared to a more basic controller.

This highlights the importance of other factors like impact feedback in VR motor learning. The findings prompt further investigation into the roles of various sensory inputs in VR to improve the effectiveness of VR training tools for motor skills.

Contents

Chapter 1

Introduction

The world of sports training is undergoing a technological revolution, and at the forefront of this transformation is virtual reality (VR). VR offers athletes the opportunity to step into immersive, digitally-created environments that mimic real-world scenarios, providing a accessible and engaging platform for honing their skills. The potential of VR in enhancing motor learning, the process of acquiring and refining motor skills, has sparked a surge in research over the past decade. Numerous studies have demonstrated the effectiveness of VR training in improving performance and altering movement patterns across diverse sports. For instance, VR has proven particularly effective in enhancing skill acquisition and performance in areas such as dart throwing [1], [2], baseball [3], rowing [4], [5], and even gymnastics [6]. These studies provide compelling evidence for the efficacy of VR as a training tool across a diverse range of sports disciplines. The benefits of VR for sports training are multifaceted and compelling.

Firstly, VR allows athletes to practice complex and potentially dangerous skills in a risk-free virtual environment. Imagine a gymnast perfecting a challenging balance beam routine without the fear of falling or a skier navigating a treacherous downhill slope without the threat of injury. VR enables repeated practice and exploration of movement boundaries, fostering skill development while minimizing physical risks [6]. This safety aspect is particularly relevant for high-risk sports or for athletes recovering from injuries, allowing them to regain confidence and refine their skills without putting themselves in harm's way.

Secondly, VR empowers athletes to train autonomously, free from the constraints of time, location, and the availability of coaches or training partners. VR training systems can be accessed at any time and place, offering personalized sessions tailored to the athlete's individual needs and skill level [7]. Furthermore, VR allows for systematic variation of training parameters, providing athletes with a wider range of experiences and challenges compared to traditional training methods [8]. For example, a golfer could practice putting on different virtual greens with varying slopes and speeds, or a basketball player could rehearse shooting under pressure with a virtual crowd cheering or jeering. This flexibility and adaptability make VR training an valuable tool for athletes of all levels.

Thirdly, VR provides athletes with real-time feedback on their performance, enhancing self-awareness and promoting rapid skill refinement. Visual cues, such as the trajectory of a ball or the position of body segments, provide immediate information about movement accuracy and efficiency [9]. Additionally, VR systems can incorporate customized feedback mechanisms, delivering tailored guidance at optimal moments to accelerate the learning process [3]. For instance, a rowing simulator could provide haptic feedback on the user's stroke technique, alerting them to deviations from the ideal pattern, or a tennis VR system could highlight the player's racket angle at the point of contact with the virtual ball. This immediate and specific feedback is crucial for identifying and correcting errors, leading to faster skill improvement.

Despite the growing body of evidence supporting the effectiveness of VR in sports training, key questions regarding its optimization remain. Researchers are actively investigating how factors like the visual fidelity of the virtual environment [8], [10]–[13] and its resemblance to real-world settings [14] influence motor learning and skill transfer. Studies have explored how varying levels of visual detail, realism of physics simulations, and the presence of virtual crowds or opponents can impact the user's experience and learning outcomes.

A critical aspect often overlooked is the role of real-world objects integrated within VR environments, particularly their impact on the user's haptic experience and subsequent motor learning outcomes [15]. While visual fidelity plays a significant role in creating an immersive VR experience, the sense of touch and force, known as haptic feedback, is equally crucial for developing a natural feel for the movement and enhancing skill acquisition.

Imagine practicing golf putting in VR. Are you using a generic controller that vaguely resembles a putter or a real golf club fitted with sensors? This seemingly minor difference can significantly impact how you learn the skill. Real-world objects in VR offer a unique advantage: they provide realistic haptic feedback, the sense of touch and force, which can be crucial for developing a natural feel for the movement. This haptic feedback encompasses not only the weight and shape of the object but also the sensations experienced during the interaction with the virtual environment, such as the impact of the club hitting the ball. The lack of realistic haptic feedback can lead to a disconnect between the visual and tactile experiences, potentially hindering the learning process.

This study focuses on the impact of incorporating real-world sports equipment into a VR system on motor learning. We investigated how using a real golf putter as a VR controller, compared to a traditional controller, affects both motor learning performance and the user's movement control within a virtual golf putting task. By comparing performance outcomes across these conditions and analyzing kinematic data, we aimed to unravel how different VR setups influence skill acquisition and how these outcomes compare to real-world practice.

This research delves into the complex interplay between haptic feedback and motor learning in VR. Our findings provide valuable insights for optimizing VR training interventions, leading to the development of more effective and realistic VR systems not just for sports training, but also for various other domains like rehabilitation, skill acquisition, and human-computer interaction.

Chapter 2

Background

This chapter provides a theoretical foundation for understanding the intersection of virtual reality (VR) and motor learning, specifically its application in sports. It begins by defining ”virtual reality” and ”motor learning,” establishing a shared understanding of these key concepts. The chapter then delves into the theoretical framework of motor learning, exploring its phases and established assessment methods. A novel framework for analyzing VR's role in motor learning is introduced, integrating Newell's theory of coordination structures with the unique aspects of VR [16]. Finally, the chapter focuses on the crucial role of feedback in VR, particularly highlighting the significance of haptic feedback and its influence on both performance and kinematic patterns.

2.1 The Nature of Virtual Reality and Its Constituent Elements

Virtual Reality (VR) offers an innovative and immersive approach to interacting with digital environments, providing users with experiences that can closely mimic or entirely diverge from the real-world. Defined broadly, VR is ”a digitally constructed environment that immerses users in an alternate setting, facilitating a sense of presence—mentally, physically, or both” [17]–[19]. This immersive environment is constructed through the synthesis of computer-generated visuals, sounds, and haptic feedback, engaging users in interactive experiences using their sensorimotor capabilities [12], [20], [21].

Rather than merely duplicating reality, VR aims to replicate essential aspects of real-world tasks and environments, including perceptual cues and behavioral constraints, while intentionally omitting elements such as actual risk and expense, thus providing a safe, cost-effective simulation for various applications [12], [22], [23]. However, this definition leads to a new question: How do we measure the extent to which VR systems replicate the real-world during research?

2.1.1 Fidelity in Virtual Reality

Fidelity is one of the most important concept in virtual reality , represents the degree to which a virtual environment faithfully replicates real-world experiences. The Merriam-Webster dictionary defines fidelity as ”1: a. the quality or state of being faithful; b. exactness in details” and ”2: the degree to which an electronic device (as a record player, radio, or television) correctly reproduces its effect (as sound or a picture).” The vast majority of uses of fidelity in VR point to the second definition. As defined by Perfect et al. and Gray et al., in the context of VR, fidelity encompasses not only the accuracy of visual and auditory reproduction but also the broader user experience, including perceptual, cognitive, and behavioral responses [24], [25]. In essence, high-fidelity in VR strives to create a virtual world that feels authentic and elicits responses similar to those experienced in the corresponding real-world scenario [26]. However, the term ”fidelity” often lacks precision in practical application. For example, in many studies, VR environments are often judged to be “high-fidelity” if they provide a detailed, realistic visual scene [27]. However, if the virtual environment does not induce a mental state or kinematic state corresponding to reality, can it still be called “high-fidelity”? To make the concept of fidelity clearer, Harris et al. categorized the fidelity of VR systems into four categories [12]:

1. **Physical Fidelity:** This dimension pertains to the accuracy and realism of the virtual environment’s physical properties. It encompasses the visual details, object behavior, adherence to physical laws (e.g., gravity, collisions), and the overall believability of the virtual world. High physical fidelity is paramount for maintaining the illusion of reality, preventing jarring inconsistencies like clipping through objects or unrealistic object interactions. This dimension most closely aligns with the traditional understanding of fidelity as visual realism.

2. **Psychological Fidelity:** Beyond physical appearances, psychological fidelity focuses on replicating the cognitive demands and perceptual processes involved in the real-world task. This includes factors such as gaze patterns, attentional allocation, decision-making processes, and the overall cognitive workload experienced by the user. Crucially, psychological fidelity assesses whether users exhibit similar cognitive and perceptual behaviors in both real and virtual environments [28]–[30]. A strong sense of presence, where users perceive the virtual environment as real, significantly contributes to achieving high psychological fidelity.

3. **Affective Fidelity:** This dimension encompasses the emotional responses evoked by the virtual experience. A high-fidelity VR simulation should elicit emotions congruent with the corresponding real-world scenario. For example, a VR flight simulator designed for pilot training should induce realistic levels of stress and anxiety associated with challenging flight conditions. Similarly, a VR game aiming to evoke excitement should trigger physiological and participantive responses comparable to real-world exciting experiences.

4. **Ergonomic and Biomechanical Fidelity:** This dimension addresses the physical interaction between the user and the virtual environment. It considers whether the VR system allows for natural and realistic body movements, promoting proper biomechanics and minimizing discrepancies between real-world and virtual actions. Factors such as the design of VR controllers, tracking accuracy, and the mapping of user movements to virtual actions contribute to ergonomic and biomechanical fidelity.

Furthermore, in the specific context of VR-based motor learning, fidelity must be evaluated in relation to the specific training goals [12], [23]. While striving for high-fidelity is generally desirable, maximizing all dimensions is not always necessary or practical. The optimal level of fidelity depends on the target skill and the desired learning outcomes. For instance, training a complex motor skill like a golf swing necessitates high ergonomic and biomechanical fidelity, allowing for realistic movement execution. Conversely, training a primarily cognitive skill may prioritize psychological fidelity over physical realism. Therefore, the virtual environment should be designed to be ”as real as necessary” to achieve the desired training outcomes, whether it be perceptual-motor skill acquisition, stress habituation, or investigating sensorimotor processes [31]–[33].

2.2 Motor Learning: Definitions, Phases, and Measurement

In this section, we will delve into the concept of motor learning and examine how VR can facilitate this process.

As discussed earlier, VR has been widely adopted in the motor learning domain to help athletes enhance their performance. Motor learning, extensively studied over decades, provides a robust framework for understanding the internal processes that lead to stable and lasting improvements in motor performance. Unlike VR, which is a relatively new field, the concepts and terminology in motor learning are well-defined and widely accepted. This section explores key definitions of motor learning, outlines its phases, and discusses the methodologies used to assess learning and performance.

By examining both classical and contemporary theories of motor learning, we aim to elucidate how VR can be effectively utilized to enhance skill acquisition and transfer in athletes. Through detailed discussions on the phases of motor learning and the ART measures — acquisition, retention, and transfer tests — this chapter provides a comprehensive overview of how motor learning is studied and evaluated [34]. Furthermore, we will explore the challenges and opportunities presented by VR in this context, emphasizing the critical factors that contribute to successful training transfer from virtual environments to real-world applications.

2.2.1 Defining Motor Learning

Edwards et al. describe *motor learning* as the internal processes that lead to the acquisition and improvement of motor skills. This involves a relatively stable or lasting change in performance or ability, which is achieved through practice or experience [34]. Similarly, Shmuelof et al. define motor learning as ”a durable improvement in motor skills resulting from practice” [35]. This process involves the creation of detailed motor plans that guide initial release movements and the systematic reduction of movement variability through the use of sensory feedback to fine-tune actions [36].

2.2.2 Phases of Motor Learning

The process of motor learning is commonly understood to progress through three distinct phases, as initially proposed by Fitts and Posner, and subsequently refined by other researchers in the field of motor control and learning [36]–[38]. These phases are characterized by different cognitive and physical demands, reflecting the learner's progression from novice to expert:

1. **Cognitive Phase:** This initial stage, also known as the verbal-cognitive phase, is marked by rapid improvements in performance. The learner focuses intensively on understanding the task requirements and forming a basic mental representation or motor program of the skill [37]. During this phase, the learner relies heavily on explicit, declarative knowledge and verbal cues. Movements are often slow, jerky, and inefficient as the learner experiments with different strategies. There is a high cognitive load as the learner consciously processes large amounts of information. Performance is inconsistent, with many errors, but improvements are rapid [38].

2. **Associative Phase:** In this intermediate stage, also called the motor stage, the learner refines the motor skill representation established in the cognitive phase [37]. Enhanced error detection and correction mechanisms are developed, and the learner becomes more adept at using sensory feedback to compare actual movement with intended output, allowing for real-time or subsequent corrections. Movements become more fluid, consistent, and energy-efficient. Cognitive demands decrease as some aspects of the skill become more automatic. The rate of improvement slows compared to the cognitive phase, but performance continues to enhance steadily [38], [39].

3. **Autonomous Phase:** The final stage, also referred to as the automatic stage, represents the pinnacle of skill acquisition. In this phase, movements become highly automated, consistent, and efficient, indicating advanced motor learning. The skill can be performed with minimal conscious attention, allowing the performer to focus on other aspects of performance or even secondary tasks. The learner can adapt the skill to varying environmental conditions with ease. Further improvements in performance are typically small and may require extensive practice or specific interventions [37], [38].

Motor learning, the process of acquiring and refining motor skills, is not a singular event but rather occurs in distinct stages. Among the various models developed to explain this progression, Fitts and Posner's three-stage model is widely recognized for its applicability to learning complex tasks, such as golf putting [36]–[38]. Each stage, marked by unique cognitive and physical demands, charts the learner's path from novice to expert.

Cognitive Phase: In the initial stage, conscious thought and deliberate effort dominate the learning process. The learner is primarily focused on understanding the fundamental requirements of the task and formulating a basic movement plan [37]. External inputs, such as visual demonstrations and verbal instructions, are critical at this stage. In golf putting, for example, the learner attends to grip, stance, and the alignment of the putter with the target, as illustrated in Delay et al.'s research on movement control in putting [40]. Movements tend to be erratic, inconsistent, and prone to errors as the individual experiments with various strategies. During this phase, verbal self-talk and feedback from coaches or training aids play a vital role. While rapid initial improvements are common, performance remains highly variable and unpredictable [38].

Associative Phase: With continued practice, the learner transitions into the associative phase, where the focus shifts from conscious processing to refining movement patterns and improving consistency [37]. Sensory feedback, particularly proprioceptive information (the sense of body position and movement), becomes increasingly crucial for detecting and correcting errors. In the context of golf putting, this phase involves developing a more consistent stroke and cultivating a better feel for the amount of force required to control distance. The learner's visual attention also becomes more selective, efficiently focusing on key environmental cues, as demonstrated in research on the ”quiet eye” in putting [41], [42]. Performance stabilizes, variability decreases, and errors become less frequent as the learner refines their technique [38], [39].

Autonomous Phase: After extensive practice, the skill enters the autonomous phase, where execution becomes largely automatic, requiring minimal conscious attention. In this stage, the golfer can perform the putting stroke with fluidity and consistency, easily adapting to variations in green speed and slope [37], [38]. As the physical execution of the task requires less cognitive effort, attentional resources can be redirected to other aspects of the game, such as reading the green or planning subsequent shots. Performance improvements during this phase tend to be more gradual, yet the skill becomes highly resistant to forgetting. It's important to note that the progression through these phases is depending on the complexity of the skill and individual differences. Moreover, different components of a complex motor skill may be at different phases simultaneously [43].

Achieving an autonomous level of performance in complex skills like golf is often a lifelong pursuit [43]. Karlsen et al.'s research on elite golfers underscores the significance of consistent stroke mechanics in attaining high levels of performance in putting [44].

2.2.3 Assessing Motor Learning

It is important to note that the ”acquisition” of motor skills at the end of training is not the same as learning, and the most important indicator of ”learning” is to what extent the acquired skills are retained and transferred [34]. Therefore, a methodology for assessing learning from performance is essential. Edwards et al. suggest that learning can be assessed by three different measurements: *acquisition tests*, *retention tests*, and *transfer tests*, collectively known as ART measures [34]. A typical motor learning study should contain all three components since each test provides equally important but different insights [34]. Figure 2.1 illustrates the ideal research design for assessing motor learning through Acquisition, Retention, and Transfer (ART) measurements.

Acquisition of Motor Skills Acquisition measurements are employed during the initial release learning phase, focusing on how quickly and accurately a new skill is acquired. It is worth noting that acquisition measurements are measurements of performance rather than learning [34]. This phase is crucial for understanding the immediate effects of practice and for establishing a baseline of skill proficiency [45].

In the context of golf, this might involve tracking changes in radial error, club head speed, or swing consistency over a series of putting trials. While valuable for monitoring progress, acquisition scores are influenced by temporary factors like fatigue or motivation and may not accurately reflect long-term learning. In our study, we use acquisition data primarily to establish baseline performance and to monitor the immediate effects of the different VR controllers.

Retention of Motor Skills Retention measurements are conducted after a certain period without practice to evaluate how well the learned skill is maintained over time [45]. This measurement is vital for assessing the durability and stability of the learned skill, providing insights into the long-term impacts of the initial release learning phase [34]. However, in actual VR experiments, the retention test, which is conducted before the transfer test to evaluate the effects of VR training in virtual environments, is often ignored and replaced by a ”new” retention test (i.e., retention test for transfer effects) conducted after the transfer test to assess the maintenance of the effects of VR training in real-world environments. This reflects the current research interest in the transfer of skills from virtual to real-world settings and their retention in the real-world, rather than their retention in the virtual world. As of now, the author has not found any study of the impact of this different test order on the validity of VR-based motor learning research.

Returning to the golf putting example, a retention test would involve measuring putting accuracy after a day or week without practice. Superior retention in one group, for example, would suggest that intervention contributes to more durable learning. In this study, we employ a retention test 24 hours after the training session to assess how well participants maintain their putting skill.

Transfer of Motor Skills Transfer measurements are employed during the last learning phase and are particularly significant in motor learning, as they assess the extent to which learned skills can be applied to different contexts or tasks that were not explicitly part of the initial release training [46].

Two different theories exist for the transfer of motor skills. Classical transfer theories (e.g., *Identical elements theory* proposed by Thorndike) state that sensory differences in virtual reality can impede the transfer of motor skills, implying that to maximize transfer, everything in the real-world should be simulated as realistically as possible to provide identical stimuli in the virtual environments [47]. Some research findings support this theory. For example, Farley et al. observed that optimal learning experiences occur when the movements closely resemble the target skill and the environmental conditions replicate the target context. If practice conditions are altered, the previously developed movement plan is no longer appropriate for successful performance [7].

However, findings from numerous studies challenge the traditional theory. Some researchers found that when certain critical factors in real-world sports were drastically changed in VR, athletes not only realized the transfer of motor learning but also experienced increased effectiveness of the transfer (e.g., the weight of the VR racket, screen resolution, etc.) [1], [3], [48]. These findings align with the *Structural learning theory*, which posits that humans are adept at identifying recurring patterns within varying environments through sensory-motor experiences and leveraging these patterns to efficiently transition to new tasks. Structural learning decreases the search space that a human must explore to adapt to a new task. By recognizing and applying these uniform features, the complexity of the learning process is reduced, leading to quicker mastery of tasks that have a similar framework. Consequently, structural learning serves as a method for enhancing the ability to ”learn how to learn” and to seamlessly switch between tasks that have a common underlying structure [49]. In VR-based motor learning research, this theory suggests that we unconsciously generalize the commonalities between virtual and real-world environments and apply what we learn to real-world tasks with less loss. The study by Bürger et al. on balance beam exercises provides strong evidence for this theory, showing that skills adapted in virtual reality could be transferred to real-world tasks and vice versa as athletes comprehended the similarities between the virtual and real environments of gymnastics [6].

However, Harris et al.'s study reveals some interesting phenomena that cannot be explained by the two theories above. They found that skills mastered by the participants could be transferred from virtual reality to the real-world but not in reverse [50]. According to traditional theories, the large sensory gap between VR and the real-world should make transfer impossible. On the other hand, according to the structural learning theory, transfer should be possible in both directions because the shared elements between the virtual world and the real-world have not changed. Clearly, the experiment's results cannot be explained by either theory. Harris cites the phenomenon of *Dual adaptation* summarized by Welch et al. in their 1998 study of the human vestibular-ocular reflex, which suggests that ”adjusting to a new sensory environment becomes quicker with more repeated experiences” [51]. In Harris et al.'s context, this phenomenon means that participants will adapt more quickly to the addition of feedback (from VR to reality) than to the reduction of feedback (from reality to VR). *Dual adaptation* implies that inconsistencies in the stimulus elements of the learning and transfer environments can seriously affect the effectiveness of transfer, and with more repetitions, humans can better grasp the common structures of the virtual and real environments, thereby realizing more efficient transfer.

The possibility of near-transfer of motor skills (skill transfer between similar domains) from VR has been confirmed by many experiments [12], but it is widely recognized that achieving significant far transfer between distant domains is a challenging endeavor [52]. Virtual Reality (VR) training, however, typically does not pursue general domain improvements. Instead, VR focuses on replicating the actual performance environment, aiming for near transfer between closely related domains, a common objective in human learning [12].

Despite the varied perspectives in motor learning theory, the ultimate measure for any VR training setting should be its ability to facilitate effective transfer to real-world applications . Yet, the key factors that contribute to successful training transfer are still largely unexplored, as noted by Rosalie and Mueller [53]. Further, golf putting learning, as of now, there has been no research specifically on its transfer effects under VR. This study can fill this gap. These facts indicating a research gap in our understanding of how to optimize VR training environments for maximal real-world applicability .

The effectiveness of Virtual Reality (VR) training hinges on its ability to transfer learned skills to real-world scenarios [3]. However, a significant research gap exists in understanding the key factors that drive successful training transfer, as highlighted by Rosalie and Mueller [53]. This gap is particularly evident in the domain of golf putting, where the transfer effects of VR training remain unexplored. While Harris et al. propose a framework for optimizing VR training environments, empirical research specifically investigating the transfer of VR-based golf putting training to real-world performance is currently lacking. This presents a clear opportunity for research to investigate and bridge the gap between virtual and real-world putting performance [12].

2.3 VR - motor learning framework

If one wants to combine motor learning with VR, it is necessary to explore the origins of motor learning - coordination and control. Unlike virtual reality, the field of coordination and control has been researched for more than a century since Thorndike's theory of identical elements, and one of the most iconic frameworks is the theory of coordination structures proposed by Newell in 1986. Newell et al. emphasize that some constraints will determine the development of coordination and action. That is to say, when people perform motor learning, they always look for a stable coordi-

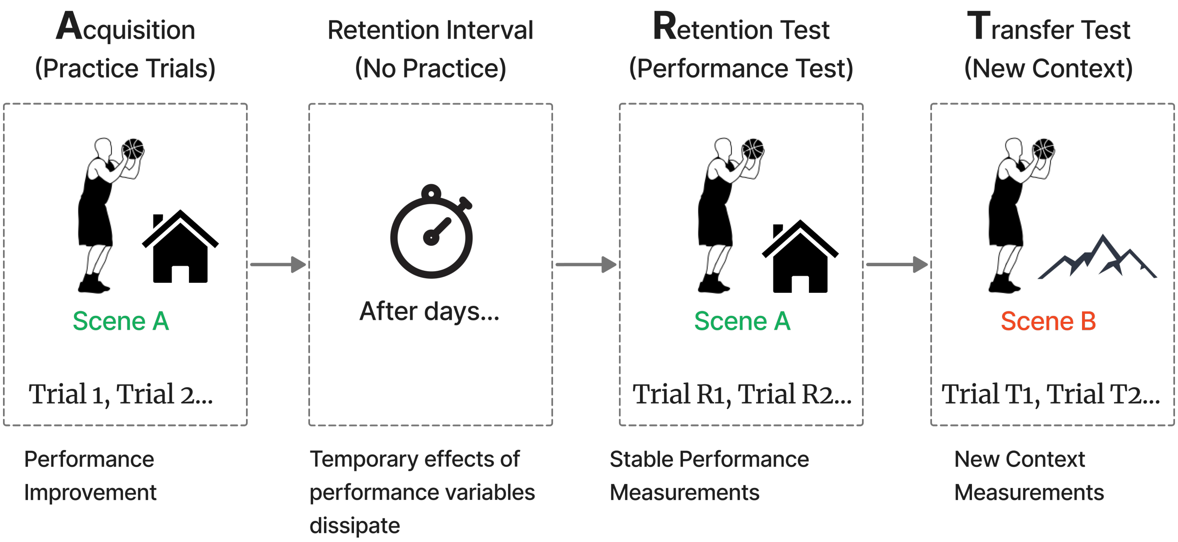


Figure 2.1: This figure illustrates the ideal research design for assessing motor learning using Acquisition, Retention, and Transfer (ART) measurements. In the **Acquisition** phase, participants perform a series of practice trials (Scene A) aimed at acquiring a skill, with performance improvements tracked over time. Following this, the **Retention Interval** phase involves a period of no practice ("After days...") to allow temporary performance variables to dissipate, ensuring that only permanent changes are measured later. In the **Retention Test** phase, performance is measured again in the same context as the acquisition phase (Scene A) to evaluate the persistence of learning. Finally, the **Transfer Test** phase involves testing the skill in a new context or different conditions (Scene B) to assess the adaptability of the learned skill.

nation and control mode(i.e., movement or cognitive pattern) to adapt to the current constraints [16]. Newell et al. further state that there are three kinds of constraints on the interaction of human sensory perceptions of the stimulus and the way they coordinate their movements: *organism* (such as the physiology of the body system), *environment* (the physical and social-cultural space where the body operates) and *task* (the regulations or criteria that shape the execution of the skill), as shown in Figure 2.2(a). [16].

When applying VR to motor learning research, we must clarify the role that VR plays in motor learning. Slater et al. propose a novel but useful definition of virtual reality, which is that virtual reality is a technological system that can refer to an already existing real-world environment, replacing the sensory input of a person and thus altering the meaning of the person's motor output [54]. This definition stands on a cognitive-behavioral viewpoint, making it distinct from the traditional hardware-software-based definition of VR, which enables us to integrate VR systems designed for motor learning into Newell's framework. That is, when virtual sensory inputs generated by virtual reality technology replace real-world sensory inputs, the meaning of the original three constraints is transformed into another dimension. It disrupts the old steady state and can force the body to search for new patterns of stable coordination and control in the virtual dimension to adapt to the newer constraints, thus altering the person's original motor output. This perspective allows us to regard VR systems as new *constraints* in the context of motor learning, as shown in Figure 2.2(b). Therefore, we can analyze sports virtual reality systems from the perspective of the three constraints proposed by Newell et al.: *environment*, *individual* (organism), and *task* [16]. Some pilot studies have already applied the above concepts in their research, for example, Drew et al. claimed virtual environments may offer different learning constraints compared to the real-world [1].

Many previous attempts to build a VR framework for sports have also involved the concepts mentioned above. For example, Neumann et al. proposed a model of interactive virtual reality (VR) in sports and sport-related exercise. In addition to having three constraints: the sports task, environments, and the athlete, the model refines the environmental constraints into virtual and non-virtual environments. Neumann et al. point out that most of the research on the application of VR in sports has neglected the factor of non-virtual environments [19].

However, the model proposed by Neumann et al. was designed for broad sports VR and did not incorporate unique concepts of VR motor learning such as "retention" and "acquisition" into the model. For this reason, we developed a new framework focused on motor learning research, as shown in Fig 2.3. This framework centers on motor skill learning, lists three factors that influence motor skill learning in virtual environments versus three factors that influence motor skill learning in real envi-

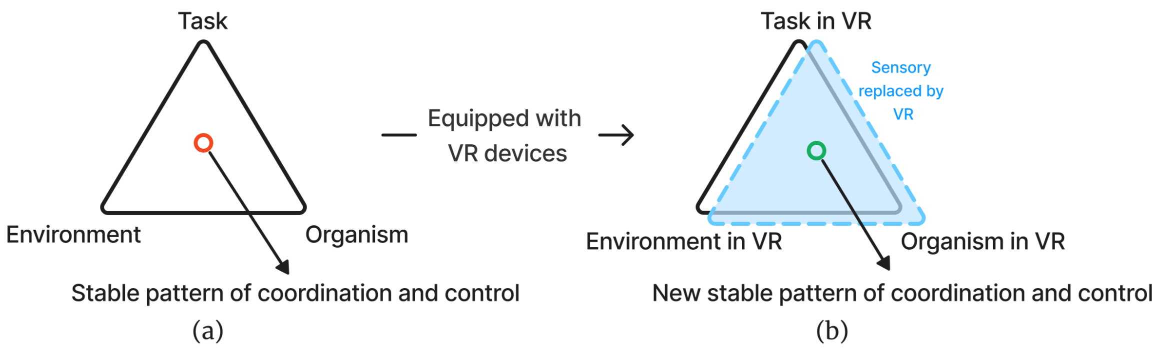


Figure 2.2: VR System in Motor Learning [15]. **Environment** encompasses both the virtual environment, shaped by VR technology, and the real-world environment in which the VR experience takes place. **User** refers to the individual engaging in the VR experience, incorporating their physical capabilities, prior experiences, and cognitive processes. **Task** represents the specific motor skill being learned, with its inherent rules and objectives.

ronments and demonstrates nine potential bilateral relationships between them that may have an impact on motor learning. The acquisition, retention, and transfer of motor skills are realized through the interaction of these six factors. Here, we categorize the six factors into three groups according to environment, user, and task, and present how the interaction between them affects motor learning.

2.4 Feedback in VR

Real-world environmental constraints, such as gravity and lighting, are inherently static and unchangeable [16]. In contrast, virtual reality (VR) provides a dynamic alternative, enabling researchers to manipulate environmental factors and examine athletic performance under various conditions, including replicating specific game scenarios [7]. When introducing the concept of fidelity into this framework, fidelity in the context of VR motor learning can be further defined as the degree to which a VR system replicates the physical, psychological, affective, and biomechanical constraints of the real-world. A high-fidelity VR environment, therefore, seeks to recreate the complete sensory experience of its real-world counterpart. For instance, perfect visual fidelity would require an exact replication of all visual information available in the real environment.

Since our perception of the VR environment is entirely mediated by the feedback provided by the VR system, the fidelity of this feedback is critical in determining the overall fidelity of the VR system. As a result, most researchers begin by examining

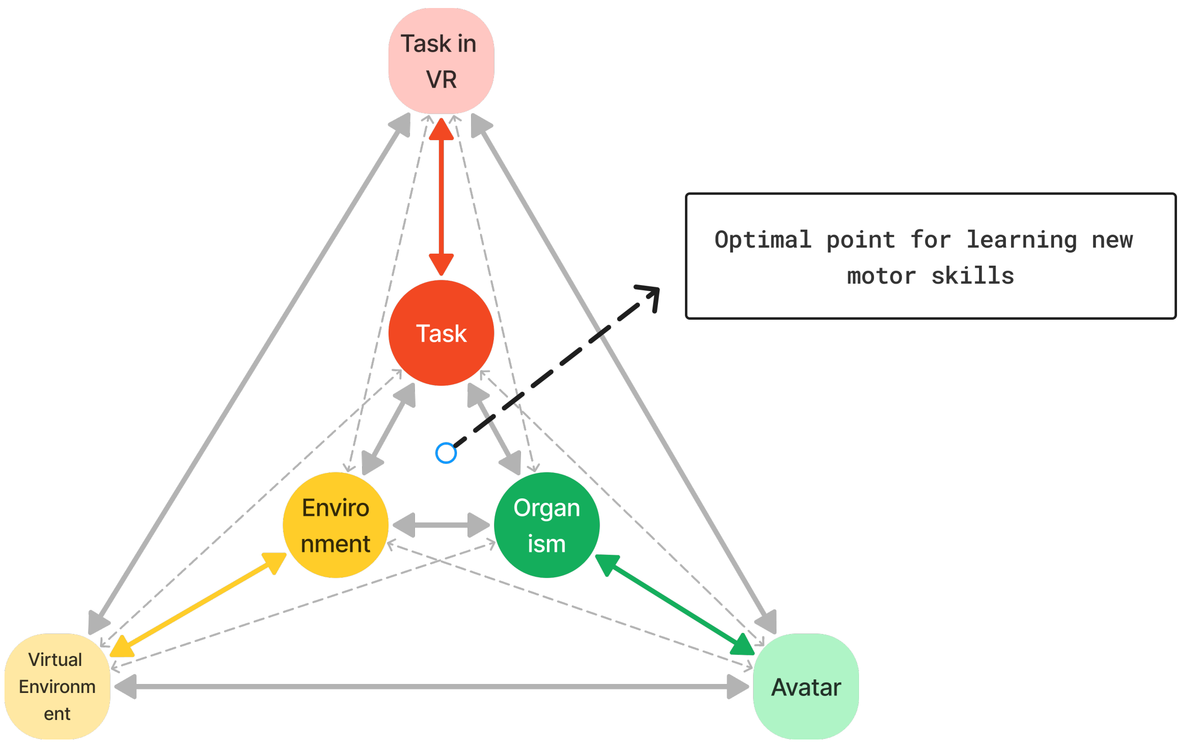


Figure 2.3: Interactive virtual reality (VR) models that target motor skill learning, show the relationship between components in the virtual environment and components in the real environment, where the solid line represents a direct correlation between the two factors and the dashed line represents an indirect correlation. The acquisition, retention, and transfer of motor skills occur in the interplay of these six factors. [15]

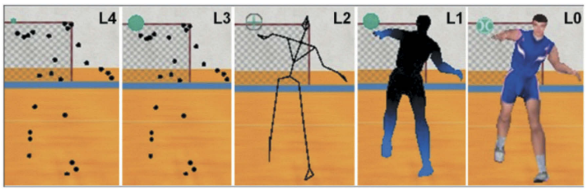


Figure 2.4: Five different visual fidelity level of a thrower by Vignais et al. [48], [55]: a textured reference level (L0), a non-textured level (L1), a wire-frame level (L2), and two moving point-light display (MLD) levels with varying ball sizes (L3 and L4).

the feedback mechanisms within VR systems to assess how varying kinds and levels of fidelity in environmental variables affect motor learning. However, significant disparities exist in the volume of research on different types of feedback: visual and auditory feedback have been much more extensively studied than haptic feedback. Researchers have developed a detailed understanding of the connections between visual and auditory feedback and motor learning, building a comprehensive framework that accounts for factors such as display medium, refresh rate, field of view, and their effects on motor performance. In contrast, studies on the relationship between haptic feedback and motor learning remain limited and fragmented [5].

A prerequisite for systematic research on feedback fidelity is the development of appropriate metrics. While methods for assessing the fidelity of visual feedback have been proposed, as depicted in Figure 2.4, a well-established system for evaluating the fidelity of haptic feedback is still lacking. This gap can be attributed to the complexity of haptic perception, which encompasses a broad range of sensations such as temperature, pressure, and discomfort, making it far more intricate than the relatively well-defined auditory and visual senses. Accurately simulating haptic sensations requires replicating all these aspects, which, with current technology, remains rudimentary at best.

2.4.1 Haptic Feedback in VR

The complexity nature of haptic feedback has led to ambiguity in researchers' definition. Burdea et al. defines haptic feedback as referring to both **force feedback** (simulating object hardness, weight, and inertia) and **tactile feedback** (simulating surface contact geometry, smoothness, slippage, and temperature) [56]. However, the vast majority of researchers have adopted a narrow definition of haptic feedback in their studies of VR systems, i.e., haptic feedback is force feedback that is actively generated by the interaction device, in the form of vibration, pressure, etc. However, they ignore the fact that the interaction device itself can also passively provide

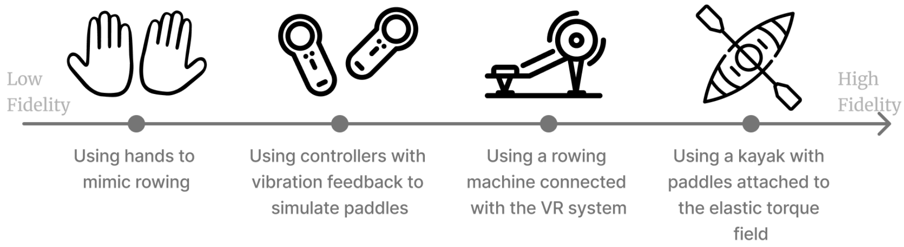


Figure 2.5: An example of different haptic fidelity levels for a rowing task in a virtual reality system

force feedback and tactile feedback. In other words, under a more accurate definition, haptic feedback includes not only feedback actively generated by the system, but also attribute information that the user can passively receive from the interactive device, including weight, shape, material, etc.

The limited evidence suggests that when the fidelity of the haptic feedback in VR systems is high, it can have the positive effect of shaping the virtual environment. In the rowing system developed by Sigrist et al., the user is required to stroke a real oar [5]. The outer end of the paddling device is connected to a parallel sensor via five ropes. The sensor uses the tension and displacement data of these ropes to calculate the horizontal and vertical angles of the paddle in real time, and applies a different amount of force on each rope to realize haptic simulation and simulate the water resistance during paddling. The haptic information provided by this system is highly similar to what we feel when rowing in the real-world, which significantly improved the fidelity of the environment. Thus we can say that haptic feedback affected motor learning in this experiment by influencing the environment.

2.4.2 Haptic Feedback from Real-World's Objects

Unlike visual feedback, it is difficult to develop a one-size-fits-all metric for measuring the fidelity of haptic feedback due to the complexity of the sense of touch itself. Therefore, measuring the degree of haptic fidelity in relation to real sports equipment may be a better solution. 2.5 depicts the different fidelity levels of haptic feedback generated by different real-world interaction objects, using rowing as an example.

The introduction of haptic feedback does not always have an impact on the fidelity of the environment. When the fidelity of the haptic feedback is low, instead of effectively contributing the virtual environment, the haptic feedback changes the task and shapes it into a new task that is different from the real-world motor task. For example, for commercial VR platforms, haptic feedback is often carried by controllers. The haptic feedback provided by these controllers is very scarce, and they can neither convey force information such as hardness and weight, nor tactile information such as material and temperature. The primary haptic feedback of the controller is the vibration generated by the vibration motor. For example, for a rowing VR system, the haptic feedback is that the controller vibrates when the oars touch the water. In contrast, in the real-world, when we hold the oar in our hands, we can feel the weight and material of the oar. Further, when the paddle enters the water, we also feel a significant change in force feedback. Obviously, the vibration feedback provided by the VR controller is completely different from the haptic feedback provided in the real-world, and the "touch-water vibration" is added to the VR paddling task as augmented feedback that does not exist in the real task. In other words, the task was changed when the real task was migrated to VR. In this case, the haptic feedback serves more as a cue to the state of the task in the virtual world, rather than shaping the virtual environment. It is worth noting that when conducting research on haptic feedback in VR, it is important to focus not only on the changes in the fidelity of the virtual environment, but also to take into account the integrity on the nature of the sport when migrating the sport task from reality to VR.

Many researchers have tried to incorporate real sports equipment into sports VR systems with a view to building a mixed reality (XR) system. This has the advantage of immersing the user in a virtual environment while providing haptic feedback with the highest degree of fidelity. For example, Harris et al. experimented with the use of real golf clubs as the interaction device for a VR golf system, and the results revealed that the participants' putting accuracy was significantly improved after the training [12]. In addition, Gray et al. used a real baseball bat for batting training in a VR baseball system, and the final test revealed a significant improvement in the participants' batting performance [3]. However, this approach is not perfect, for one thing, none of the systems mentioned above have the ability to simulate the feeling of impact when the ball comes into contact with the bat or putter; and secondly, they are more demanding on the type of sport, and are unable to simulate sports such as rowing, swimming, and other sports that have stringent requirements on the field.

When real equipment is impractical, machinery mimicking real equipment, like rowing machines, can be used. These devices offer feedback fidelity between real equipment and controllers. Arndt et al. built a VR rowing training system based on a rowing machine. As stated by the authors, the rowing machine has a high haptic fidelity that reflects well the resistance encountered by the oars when rowing in VR.

The results showed significant improvements in the technical aspects of rowing for the participants. However, there is a problem with the system: the rowing motion on the rowing machine is not exactly the same as real rowing. [4]. Similarly, Sigrist et al.'s rowing machine study modified to mimic real rowing experiences, showed significant spatial error reductions with feedback training [5]. In summary, all of these studies suggest that the richness and fidelity of haptic feedback may have some positive relationship with motor learning performance.

In addition to being used as a simulation of how an avatar feels in a virtual environment, haptic feedback can sometimes be used as augmented feedback to give information related to the user's performance directly to the user. This practice also makes a strong positive contribution to motor learning. For example, the paddling system by Sigrist et al. guides users to learn to paddle in a virtual environment by using vibration and force feedback to alert them when their paddles deviate from a preset trajectory. Finally, the authors conclude that motor learning and performance can be effectively facilitated by providing tactile guidance for complex movements [36]. Force feedback systems have shown significant improvements in task performance compared to vibrotactile or visual feedback alone, indicating the potential of haptic augmented feedback to enhance motor skills [57]. However, integrating haptic feedback in VR remains a challenge due to the limited range of sensations current technologies can simulate compared to real-world experiences [57].

2.4.3 Haptic feedback and kinematic patterns

The relationship between haptic feedback in virtual reality (VR) and human kinematic patterns has emerged as a crucial area of study in motor learning research. Kinematic patterns, which describe the motion of bodies without considering the forces causing them, are fundamental to understanding how movements are performed and refined over time. Recent literature suggests that different types of VR feedback, particularly haptic feedback, significantly influence these kinematic patterns, thereby affecting the efficacy of motor learning and skill transfer from virtual to real-world environments.

Studies have demonstrated the impact of haptic feedback on kinematic patterns in various motor tasks. Markwell et al. compared VR and real-world golf putting practice, finding that participants using VR controllers exhibited similar kinematic patterns to those practicing in reality [58]. This similarity was attributed to the haptic feedback provided by the VR controllers, which effectively mimicked real-world sensory input. Brock et al. further elucidated this relationship by examining visuomotor tasks in real and virtual environments [59]. Their research revealed that the absence of end-point haptic feedback in VR resulted in slower, more exaggerated movements, underscoring the importance of tactile feedback in refining motor control and achieving natural kinematic patterns.

There have also been some studies that have found VR controllers that include less haptic information can cause kinematic patterns to deviate significantly from the real-world environment. Drew et al. explored the kinematic differences in dart throwing between VR and real-world settings [1]. Their findings indicated that VR practice, using the HTC Vive controller and a commercially available application, resulted in different kinematic patterns compared to real-world practice. While these studies provide valuable insights, research focusing specifically on how haptic feedback from VR controllers affects kinematic patterns in motor learning remains limited.

It is clear that the impact of haptic feedback on motor learning in VR environments warrants further investigation. Research centered on haptic fidelity (as shown in Figure 2.5) can provide valuable insights into how different forms of haptic feedback can contribute to skill acquisition and performance in virtual training environments.

2.5 Goals and Hypothesis

Current research highlights the importance of haptic feedback in VR-based motor learning, however, we do not understand the impact of using real-world objects as interaction media on motor learning under the VR environments. Thus, this study investigates how different levels of haptic fidelity in VR controllers impact motor learning, focusing on haptic feedback by comparing the use of real golf putter to a standard VR controller.

The rationale for selecting golf putting as the motor skill stems from several factors. First, the availability of sophisticated, commercially available VR golf simulators provides a high-fidelity training environment, enhancing participant immersion and the ecological validity of the experiment. Second, golf putting is a complex motor skill involving coordinated movements and the interplay of strength and precision [12], [44], making it a suitable task for studying multifaceted motor learning processes. Third, the distinct shape and weight of a golf putter offer a stark contrast to standard VR controllers, maximizing the potential for observing the effects of controller fidelity. Finally, the impact sensation during ball contact in real-world putting introduces an additional layer of haptic feedback, allowing for comparisons between VR and real-world training to investigate the role of such cues in skill acquisition.

In this study, we aim to determine how closely VR training with a high-fidelity controller (i.e. Controller incorporated with real worlds sports equipment) replicates the learning outcomes of real-world practice and how both compare to training with a standard VR controller. Based on the limitations of current research and our rationale for this study design, we hypothesize the following:

- **H1 (Performance):** Participants in the ConClub condition will exhibit greater improvements in putting performance compared to those in the Con condition. However, neither VR group (Con or ConClub) will achieve the same level of performance improvement as participants in the Club condition. This hypothesis reflects the expectation that increased controller fidelity will enhance learning in VR, but that the full haptic experience of real-world practice remains unmatched.
- **H2 (Kinematics):** The kinematic characteristics of participants' putting strokes in the real-world post-tests will be more similar between the ConClub and Club groups than between the Con and Club groups. This hypothesis predicts that training with the high-fidelity VR putter will lead to kinematic patterns that more closely resemble real-world putting movements compared to training with a standard VR controller.

Chapter 3

Methods and Techniques

This chapter explains the methods used to investigate the research questions in this study. We begin by stating the experimental design settings, including the equipment used (Meta Quest 3, Xsens DOT, real and modified putters), and the setup for both real and virtual golf putting environments. We also explain how we collected performance metrics and kinematic data. Finally, we outline the data processing techniques used to analyze the performance and kinematic data. This chapter aims to provide a clear and thorough explanation of our methods to ensure the findings are credible and reproducible.

3.1 Experiment Design

The experiment employs an independent group design with two experimental groups and one control group.

- **Control Group (Club Group)**: Participants in the control group trained with a real golf putter in a physical environment. They were instructed to focus on developing a consistent putting technique. Each participant stood at a designated starting position and made 75 consecutive putts toward a target located 6 meters away, using a real golf ball. No additional instructions or feedback were provided during the training to simulate a natural, self-guided practice session.

- **Experimental Group 1 (ConClub Group)**: In this group, participants trained in a virtual reality (VR) environment using a modified golf putter equipped with a VR controller. The simulation closely mimicked a real golf course, including environmental sounds and haptic feedback from the controller. Participants also performed 75 putts toward a virtual target 6 meters away, with the goal of improving their technique. Haptic and auditory feedback provided real-time sensations similar to striking a real golf ball, enhancing the immersion and training experience.

- **Experimental Group 2 (Con Group)**: Participants trained in the same VR environment as Experimental Group 1 but used standard VR controllers instead of the modified putter. Like the other groups, they completed 75 putts toward a virtual target. However, the VR controller, being lighter and less realistic in its feel, offered a different training experience. Participants received visual feedback from the VR environment but did not experience the same physical sensations as in the high-fidelity group.

In all groups, the 75 putts were completed in a single session without interruption. Participants were allowed brief rest periods between putts if needed but were not given specific feedback on their performance during training.

This independent group design allows for clear comparisons between the effects of different training tools on motor learning. Modified controllers in this context refer to controllers highly similar to actual sports equipment in terms of use, mass, and center of gravity, which will be described in detail in subsection 3.2.2.

3.2 Experimental Settings

This section describes the details of the experimental environments for both real-world and VR golf putting, including the equipment used and the venue settings.

3.2.1 Real-world golf putting

All participants completed a real-world putting test. The control group trained using golf putter in a physical environment, performing 75 putts during the training session.

The golf putter has an original mass of 350 grams and a length of 150 cm, which meets the standards of the United States Golf Association 3.1b. When training and testing happened in the real-world, participants were asked to use this putter.

For the environment, we choose the indoor laboratory as the venue for golf putting. The size of the venue is 1200 cm * 600 cm, the layout of the venue is shown in Figure 3.2. The floor of the venue was carpeted with a short pile carpet, which resembled golf grass. In the training and testing phase, participants were required to stand at one end of the field to hit the ball, and they were asked to putt the ball as close as possible to a target 6 meters away. It is worth noting that the ball does not stop as it passes over the target because the target is flush with the ground.

(a) Con: VR controllers

(b) Club: Putter

(c) ConClub: VR controller incorporate with putter

Figure 3.1: Experiment equipments

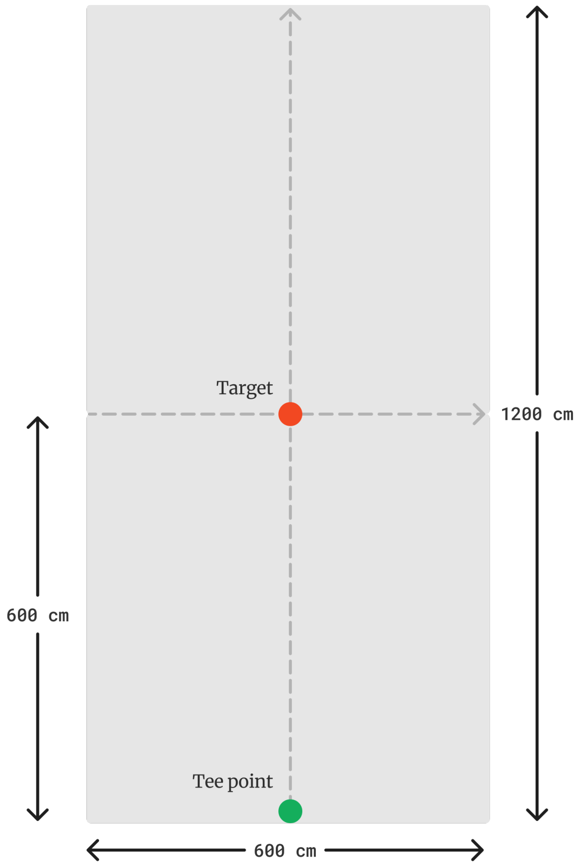


Figure 3.2: Illustration of the experimental venue

3.2.2 VR golf putting

Participants in both experimental groups trained in a VR environment using the Meta Quest 3 headset and controllers. The Meta Quest 3 is a six-degrees-of-freedom headset with a 110-degree horizontal and 96-degree vertical field of view. The controllers used differed between the two experimental groups:

- Experimental Group 1 (High-fidelity VR controllers): Participants used a modified putter, where the Meta Quest 3 Touch Pro Controller was attached to the middle of a real golf putter, closely replicating the weight and feel of the real putter (Figure 3.1c). This modification added an additional 104 grams to the original 350-gram putter.

- Experimental Group 2 (Standard VR controllers): Participants used the unmodified Meta Quest 3 Touch Pro Controller, which weighs 104 grams (Figure 3.1a). This setup was considerably lighter and less realistic in feel compared to the modified putter.

The VR simulation was powered by the GOLF+ program (developed by GOLF+ in Texas, United States), which provides a virtual golf environment with auditory and haptic feedback. Participants could hear the sound of the club striking the ball and receive vibration feedback when the club hit the ground or ball, enhancing immersion. The target was the same size and distance as in the real-world setting (6 meters), ensuring consistency across conditions.

(a) Targets in the participant's view in VR environment

(b) The counterpart of real-world controllers in VR environments

Figure 3.3: Golf Putting Environment in VR

3.2.3 Data collection

Putting performance

Traditional measurement methods for putting performance, such as those described by Walters-Symons et al., Harris et al. and Moore et al. [41], [42], [50], involve assessing **Radial Error**, which is the two-dimensional Euclidean distance between the ball and the hole. However, these traditional measurements may miss some important information, such as the accuracy of aim and amount of power when striking the ball. For the participant, the goals of the putting task can be interpreted as 1. to swing the club using just the right angle so that the ball travels a course that is in line with the line between the tee and the target. 2. swing the putter using just the right amount of power so that the ball rolls the same distance as the distance from the tee to the target. Therefore, in the present study, in order to explore more deeply the effects of different training conditions on aiming and self-perception of strength, except for radial error, we reflected the effects of motor learning through another two factors: the **Initial Release Angle** and the **Distance traveled by the ball**. The coordinate system and measurement are shown in Figure 3.4.

The Initial Release Angle, θ, is the angle between the initial release direction of the ball's motion and a reference line, typically the horizontal axis. Understanding the Initial Release Angle of the golf ball during putting is critical for analyzing putting performance. Literature indicates that initial release conditions, such as angle and speed, significantly impact the trajectory and success of a putt [60]. In golf, as in other precision sports, controlling these initial release conditions can lead to more consistent and accurate outcomes [41], [42]. A correct Initial Release Angle ensures that the ball follows the intended trajectory, thereby increasing the likelihood of a successful putt. Research in related fields, such as basketball and throwing, has shown that precise control of initial release release parameters can significantly improve performance outcomes [60]. Based on this evidence, it is also reasonable to believe that in golf, the Initial Release Angle can be a valid reflection of the participant's progress in learning putting motor skills.

The distance the ball travels is another key factor to be considered. Since the distance the ball travels is directly related to the speed of the ball, we can equivalently consider the distance the ball travels as a measure of the power of the putter. If the force of the putt is too high or too low, the distance the ball travels will deviate from the correct distance. Analyzing this value will allow us to explore the effects of training with different equipment on the perception of power.

In this experiment, we measured the coordinates of a golf ball after it was putted. The ball was placed at a fixed starting point, called the tee point. The target, located 6 meters awy, was designated as the origin of our coordinate system. The line

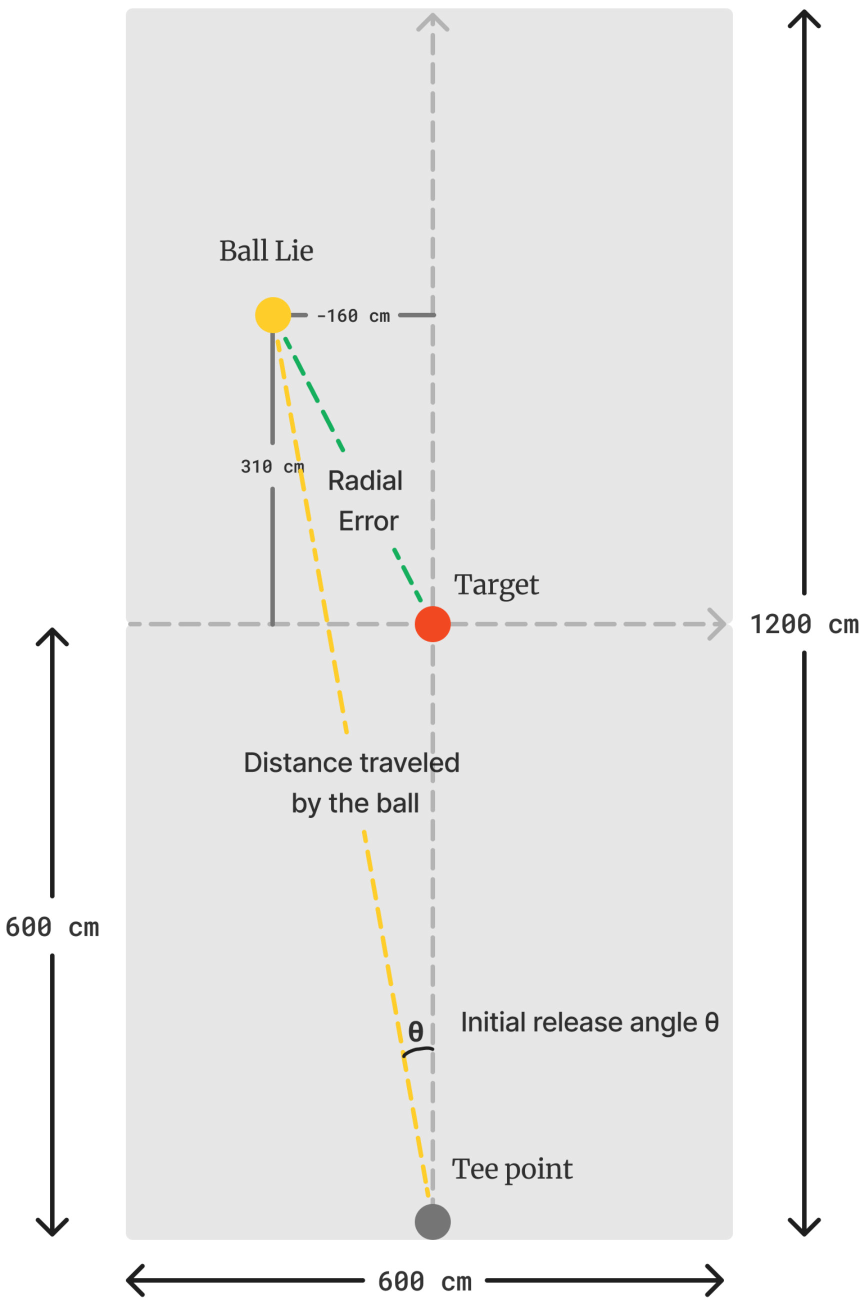


Figure 3.4: Measurement of golf ball coordinates

connecting the tee point to the target was defined as the Y-axis. Perpendicular to this, we defined the X-axis. After each putt, when the ball came to rest, we used a tape measure to determine its final position in terms of X and Y coordinates. These coordinates were then used to calculate the Initial Release Angle and the distance the ball travels.

The radial error R between the ball's final resting position and the target can be calculated using Pythagorean theorem:

$$R = \sqrt{X^2 + Y^2}$$

where:

- X is the horizontal distance between the target and the ball's final position.
- Y is the vertical distance from the target to the ball's final position.

The angle θ between the ball's final resting position and the Y-axis (the intended path) can be calculated using the arc-tangent function, which relates the opposite side to the adjacent side in a right triangle. The formula for the angle θ is given by:

$$\theta = \tan^{-1}\left(\frac{X}{Y+600}\right)$$

- X is the perpendicular distance from the Y-axis, which serves as the opposite side of the triangle.
- $Y + 600$ is the vertical distance (in cm) along the Y-axis from the ball's final position back to the tee point, which serves as the adjacent side of the triangle.

By calculating the arctangent of the ratio $\frac{X}{Y+600}$, we obtain the angle θ in radians. To convert this angle to degrees, we multiply by $\frac{180}{\pi}$.

Thus, the full formula in degrees is:

$$\theta_{\text{degrees}} = \tan^{-1}\left(\frac{X}{Y+600}\right) \times \frac{180}{\pi}$$

This angle θ represents how far the ball deviated from the intended straight path towards the target, with a positive angle indicating a deviation to one side and a negative angle indicating a deviation to the opposite side.

The distance traveled by the ball can be calculated using the Pythagorean Theorem , and the calculation process needs to take into account the horizontal and vertical components of the ball's motion from the point of the tee point to its final resting position.

The total travel distance D is the hypotenuse of the right triangle formed by the horizontal and vertical distances. The Pythagorean theorem states:

$$D = \sqrt{X^2 + (Y+600)^2}$$

- X is the horizontal distance, provided as the X-coordinate.
- $Y + 600$ is the vertical distance from the tee point to the final position.
- D is the travel distance of the ball in centimeters.

Kinematic behavior

As mentioned earlier, in the present study, we not only wished to explore the effects of different haptic feedback on performance but also to gain knowledge of the altered kinematic patterns caused by these feedback. To achieve this goal, we employed a comprehensive approach to data collection, focusing on key body segments and equipment crucial to the putting stroke.

Over the past few decades, numerous studies have investigated the kinematic patterns of different body segments, the coordination between these segments, and the resultant motion of the golf putter. One of the primary areas of focus in kinematic research on golf putting is the motion of the upper body, particularly the shoulders, arms, and hands. The pendulum-like motion of the upper extremities is often cited as a critical factor in achieving a smooth and controlled putting stroke.

According to Karlsen et al., an effective putting stroke is characterized by a predominant rotation around the shoulder joints [44]. This shoulder-dominated movement helps maintain a stable putter path and face angle at impact, which are crucial for directional accuracy and distance control. To capture this essential movement, we placed sensors on key body locations.

The sternum, located centrally on the thorax, serves as an ideal reference point for capturing the overall movement of the upper body. This central location is critical for measuring the stability and rotational motion of the shoulders and torso, which are essential components of an effective putting stroke. By placing a sensor on the sternum, researchers can obtain comprehensive data on the golfer's upper body kinematics, which can be used to evaluate their skill level and track improvements over time.

To collect this kinematic data, we used Xsens DOT sensors from Movella. These compact, wearable motion sensors, measuring 36.3 x 30.4 x 10.8 mm and weighing 11.2 grams, are equipped with a 3D accelerometer, gyroscope, and magnetometer to deliver precise 3D orientation data. The sensor coordinate system (S) is a right-handed Cartesian coordinate system that is fixed to the body of the sensor [61]. It is depicted below on Figure 3.5, with the axes labeled as x, y, and z.In this research, Xsens DOT will record the acceleration, Euler angle and angular velocity rate of change in all three directions at a sampling rate of 60hz in CSV format.

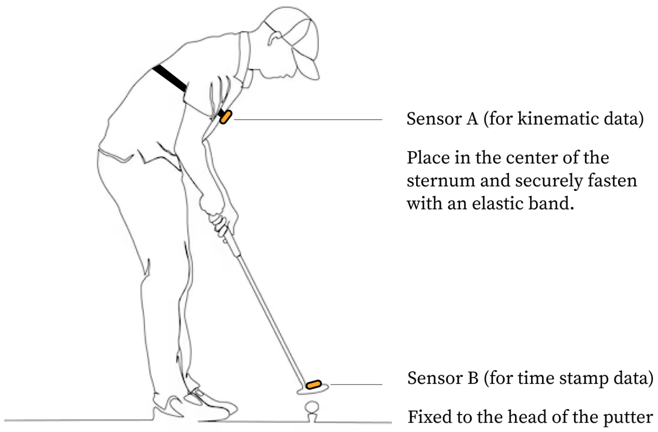


Figure 3.6: Sensor placement schematic

Figure 3.5: Xsens DOT sensor coordinate system [61]

During the experiments, participants were asked to wear close-fitting clothing to ensure accurate sensor placement. One sensor was securely affixed to the center of the participant's sternum using elastic tape to prevent any movement or slippage during the test, allowing us to precisely measure the rotational angle of the chest during the putting stroke. This enabled us to analyze shoulder-dominated kinematic patterns. Additionally, another sensor was mounted on the head of the putter to record time and displacement as the participants executed real-world putts, providing data on the critical factors identified by Delay et al. and Sim et al. [40], [62]. The placement scheme is demonstrated in the figure 3.6.

This arrangement allows us to compare the motion profiles of golfers using different devices during the three test phases. If the motion patterns using the Con-

Club are very close to those using the Club training in the real-world environment, it indicates that training with the high-fidelity controller successfully replicates the real-world putting requirements. Conversely, if there is a significant difference between the two conditions, it suggests that the high-fidelity controller may not be helpful for VR motion learning.

Interview

Upon completion of all experimental tests, participants were invited to join a brief interview designed to explore qualitative aspects of their experience during the putting training sessions. The interview comprised seven open-ended questions, tailored to differentiate based on the participant group allocations. These questions were crafted to elicit detailed insights into the participants' personal perceptions and challenges with the training process.

The interview protocol was structured around the following key areas:

1. Comfort in VR: Participants were asked about any discomfort experienced during the VR training, prompting them to elaborate on specific aspects of the VR experience that might have contributed to their comfort or discomfort.

2. Comparison of Real-World and VR Golf: Participants were asked to describe and compare their feelings and perceptions of putting in the real-world versus the VR simulation. This aimed to uncover any discrepancies or similarities in their experiences between the two environments.

3. Feedback Differences: This section focused on probing the participants' perceptions of the feedback mechanisms in both the VR and real-world settings. Participants were encouraged to detail the type, quality, and helpfulness of the feedback received in each environment.

4. Perceived Training Impact: Participants were asked about their opinions on the effectiveness of the VR training in improving their real-world putting skills. This aimed to capture their participantive assessment of the training's value and impact.

Additionally, participants were asked about the potential impact of using a putter during training, their overall opinion on whether VR helped them learn golf, and to provide any other comments about their experience.

All interviews were audio-recorded and transcribed verbatim for analysis. During the interview, speech was transcribed into text in real time for subsequent semantic analysis (see Appendix D.1 for the full list of transcripts).

3.3 Experimental Procedure

A total of 24 participants were recruited for this study. Regardless of the group, the experiment lasted two days for each participant. On the first day, they were required to take a pre-test, training and post-test, and on the second day, they were required to take a retention test and a short interview. The data collected in the experiment included basic personal information, kinematic information, performance information, and interview information. The flow of the experiment is shown in Fig 3.7:

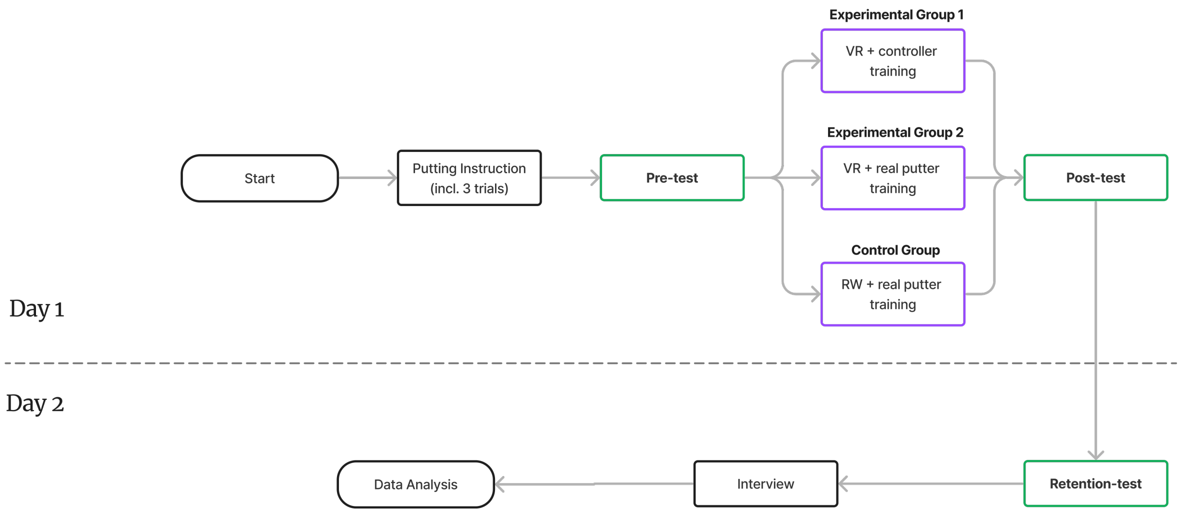


Figure 3.7: Experimental flow

3.3.1 Recruitment and experiment preparation

24 university students (include 8 females and 16 males; mean age = 25.6, SD = 2.7; max = 32, min = 20) were recruited from the University of Twente. All participants reported themselves as novice golfers. For the purposes of this study, we used Moore et al.'s definition of a novice golfer: novice golfers are people without a formal golf handicap or formal golf putting experience [63]

All participants were informed of the study details before participation and provided written consent. To ensure participants' health, additional verbal confirmation was conducted to confirm they had not experienced Cybersickness. Ethical approval for the study was obtained from the Faculty Ethics Committee before data collection began.

Prior to the Pre-test, each participant will be assigned to one of three groups. Then, each participants were asked to watch an approximately five-minute instructional video on golf putting presented by a PGA-certified instructor, which included basic instruction on grip, stance, and movement. Afterwards, the participants were

Figure 3.8: Participants performing putting training in a VR environment with Con-Club

asked to make three trial putts in order to familiarize the use of the equipment and to gain a basic feel for putting. Data from this session will not be recorded. During this process, the researcher also gave limited instruction by answer the participants' questions about putting.

3.3.2 Test Settings

The main body of the experiment consists of three testing sessions, and a training session. The testing session consisted of a pre-test, post-test and retention test, the design of which followed the motor learning measurement framework mentioned in the previous chapter. For each test, all participants were asked to make ten putts with putter in a realistic environment. Pre-test was conducted prior to the training session and the results were used as a baseline. Post-test was conducted immediately after the training session in order to examine the learning and transfer of skills. Retention-test was conducted the day after the training session to examine the retention of motor knowledge gained from the training session. the degree of retention of motor knowledge acquired.

After completing all experimental tests, participants were required to take part in a short interview designed to explore their experiences during the putting exercise. The detailed procedure for this interview is outlined in section 3.2.3, as mentioned previously.

3.4 Data Processing

The data utilized in this study were classified into three distinct categories. The first category comprises deviation values recorded during the trial phase, which reflect motor performance. The second category includes kinematic data obtained from the Xsens DOT sensor. The third category consists of transcripts from the interviews conducted. In this section, we will examine the processing and analysis methods applied to each type of data, thereby establishing a theoretical foundation for the subsequent results chapters.

3.4.1 Performance data processing

In this section, we describe the processing methods used to analyze the performance data. The analysis aimed to explore the impact of different equipment on motor learning by examining performance indicators in different groups and test phases. A total of thirty sets of data in the form of coordinates were recorded for each participant across the three tests. The data processing methodology includes data loading, descriptive statistical analysis, normality and homogeneity tests, ANOVA or non-parametric tests, post-hoc analysis, and visualization.

Performance data processing and analysis were conducted on Python 3.9. The libraries used included:

- **Pandas** for data manipulation and analysis.
- **NumPy** for numerical computations.
- **SciPy** for statistical functions and tests, essential for performing normality and homogeneity tests, as well as non-parametric analyses.
- **Statsmodels** for advanced statistical modeling, including ANOVA and post-hoc tests.
- **Seaborn** and **Matplotlib** for data visualization, creating informative plots to visualize the distribution and variability of the performance data.

Data Loading

The first step was to manually enter all the experimental data as a csv file and import it into the data analysis program. The dataset contained columns for X-deviation, Y-deviation, Group, Participant ID and Test Type. The data were structured to allow for subsequent group comparisons and test comparisons.

Data Preprocessing

Our analysis began with a comprehensive data integrity test to ensure dataset completeness and accuracy. This process involved verifying column data types, identifying duplicate entries, and confirming the correct number of trials for each participant across test phases. This critical step prevents erroneous conclusions that could arise from inaccurate or incomplete data.

In addressing data quality, we also tackled the issue of missing values, which can potentially skew results and reduce analysis validity. We employed multiple imputation to estimate missing values based on observed data, preserving the overall data structure and relationships. This method was chosen for its ability to maintain statistical power by preserving sample size and account for uncertainty in missing data estimates, offering advantages in bias reduction and estimate accuracy compared to simpler methods.

With a clean and complete dataset, we proceeded to calculate two primary performance metrics: Initial Release Angle and ball travel distance. These metrics, derived from X-deviation and Y-deviation values as detailed in Section 3.2.3, form the foundation of our performance analysis.

To quantify performance accurately, we developed deviation measures by comparing these metrics to their optimal values:

$$\text{Angle Deviation} = |\theta - 0| \tag{3.1}$$

where θ is the Initial Release Angle . The optimal angle is 0°, with larger deviations indicating less accurate aiming. It's important to note that we use the absolute value here, denoted by the vertical bars (— —). This ensures that we measure the magnitude of the deviation regardless of whether the angle is positive or negative. For example, a Initial Release Angle of 5° and -5° would both result in an angle deviation of 5°, reflecting that both are equally far from the optimal 0° angle.

$$\text{Distance Deviation} = |D - 600| \tag{3.2}$$

where D is the travel distance in centimeters. The optimal distance is 600 cm, with larger deviations indicating less accurate putts. Again, we use the absolute value to capture the magnitude of the deviation. This means that a putt that falls 50 cm short (550 cm) and one that goes 50 cm too far (650 cm) would both result in a distance deviation of 50 cm. This approach allows us to measure accuracy without distinguishing between undershooting and overshooting, as both are equally undesirable in putting performance.

While these deviation measures provide valuable insights, they do not account for potential differences in baseline performance between groups. To address this limitation and enable more meaningful comparisons, we introduced the Performance Progress Value. This metric measures improvement between tests:

$$\text{Pre-Post Improvement} = |\text{Angle DeviationPost}| - |\text{Angle DeviationPre}| \tag{3.3}$$

$$\text{Pre-Retention Improvement} = |\text{Angle DeviationRetention}| - |\text{Angle DeviationPre}| \tag{3.4}$$

We applied similar calculations for ball's travel distance deviations. In these formulas, we use absolute values for each individual Angle Deviation measurement to ensure we're comparing the magnitudes of deviations at different time points. This approach allows us to capture improvements regardless of whether the initial deviations were positive or negative.

In this framework, negative values indicate performance regression, while positive values represent improvement. For example, if a participant's Angle Deviation decreased from 10° in the pre-test to 5° in the post-test, the Pre-Post Improvement would be -5°, indicates a decrease in the deviation value, i.e., an increase in performance. Conversely, if the Angle Deviation increased from 5° to 8°, the Pre-Post Improvement would be 3°, signifying a decline in performance.

By including these progress values, our analysis can compare learning effects between groups while accounting for potential differences in initial skill levels, providing understanding of performance changes over time.

Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to summarize and understand the basic features of the data before performing more complex inferential analyses. This step involved calculating measures of central tendency and variability, and visualizing the distribution of performance scores across different groups and test phases.

In the discussion that follows, we will use these visualizations to approximate any patterns and trends that exist in the data.

Normality and Homogeneity Tests

Before conducting inferential statistical tests like ANOVA, it is essential to ensure that the data meet the assumptions of normality and homogeneity of variances. To assess these assumptions, we use boxplots, Q-Q plots, and residual analyses.

Boxplots visually assess the distribution's spread and symmetry across groups and identify any outliers that might indicate deviations from normality. Q-Q Plots compare the quantiles of our sample data against those of a theoretical normal distribution. A linear relationship between these quantiles suggests that the data are normally distributed, while deviations, particularly at the tails, indicate potential non-normality. Residual Analysis examines the residuals—differences between observed and predicted values. Residuals should be randomly distributed around zero without any apparent patterns, supporting both normality and homogeneity of variances.

Statistical test

Next, we are going to evaluate the differences in performance across different groups and test phases, and to understand the effects of different training modalities on motor learning. These tests help determine whether the observed differences are statistically significant or if they could have occurred by chance.

Parametric Test When the data did not violate the normality assumption and the variance chi-square assumption, to analyze the effects of multiple factors on our dependent variables, we employed a two-way analysis of variance (ANOVA). This statistical method allows us to simultaneously examine the impact of two independent variables and their potential interaction on a continuous outcome variable. In our study, the two-way ANOVA enabled us to assess not only the main effects of group invention and test phases factor but also whether the effect of one factor depends on the level of the other.

The two-way ANOVA partitions the total variance in the data into components attributable to the main effects of each factor, their interaction, and residual error. By comparing these variance components, we can determine whether the observed differences between group means are statistically significant or likely due to chance.

Non-Parametric Tests When the assumptions of normality and homogeneity of variances are violated, non-parametric tests offer a robust alternative. Non-parametric tests do not assume a specific distribution for the data, making them suitable for analyzing non-normally distributed data or data with unequal variances.

For this study, the Kruskal-Wallis test was selected as the non-parametric alternative to LMM. The Kruskal-Wallis test evaluates whether the distribution of ranks differs between groups. It is the non-parametric counterpart to the one-way ANOVA and is used when the independent variable has three or more groups. The test statistic H is calculated as:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} n_i \left(\bar{R}_i - \frac{N+1}{2} \right)^2 \tag{3.5}$$

where n_i is the sample size of group i, $\bar{R}_i$ is the average rank of group i, and N is the total sample size. A significant p-value indicates differences between groups.

Post-Hoc Tests

Following significant main effects or interactions, we conducted post-hoc tests to identify specific group differences. Here we adapted Bonferroni Correction as post-hoc test. The Bonferroni correction adjusts the significance level to account for multiple comparisons, reducing the likelihood of Type I errors. For m comparisons, the adjusted significance level α_{adj} is:

$$\alpha_{\text{adj}} = \frac{\alpha}{m} \tag{3.6}$$

3.4.2 Kinematic data processing

The kinematic data were obtained using Xsens DOT sensors placed on participants body and putting equipment. The raw data encompassed a comprehensive set of parameters including temporal markers, orientation data (Euler angles and quaternions), accelerations, and angular velocities. The data processing methodology aimed to extract meaningful kinematic parameters and identify key events in the putting motion. The reasons for selecting these specific kinematic parameters have been discussed in section 3.2.3. The processing of sensor data involves multi interrelated steps, as shown in the Figure 3.9 below.

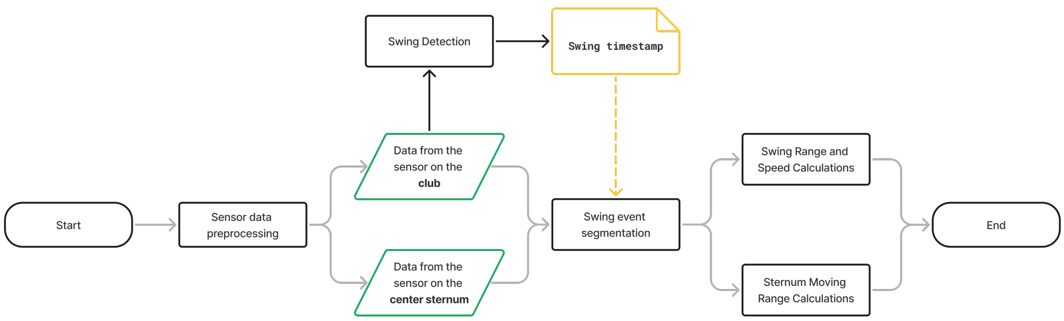


Figure 3.9: Kinematic Data Processing Flow

Data Preparation

Swing Detection

The golf swing comprises a series of complex, coordinated movements that can be systematically analyzed and segmented. Williams et al. [64] delineated eight distinct stages of the golf swing:

1. Set-Up: Initial positioning, including stance, grip, and aim adjustment.
2. Takeaway: Initiation of club movement with slow backward motion and shoulder rotation.
3. Backswing: Continuation of backward club motion with wrist, shoulder, and hip rotation.
4. Top of the Backswing: Apex of the swing, characterized by maximum body rotation and energy storage.
5. Downswing: Rapid downward club movement with simultaneous hip and upper body rotation.
6. Impact: Moment of club-ball contact, featuring partial weight transfer to the front foot and club face alignment with the target.
7. Follow Through: Post-impact continuation of forward club motion to a secondary apex.
8. Finish: Conclusion of the swing, maintaining balance and target focus.

For the purposes of our swing dynamics recognition algorithm, we identified five key moments from these stages that are particularly suitable for analysis. These critical points can be effectively localized by examining the temporal evolution of both the Euler angle about the Z-axis (Euler_Z) and the acceleration along the X-axis (Acc_X) of a sensor affixed to the putter's head.

Euler_Z is especially informative in this context as it quantifies the putter's head's rotation in the horizontal plane, capturing the essential twisting motion characteristic of the golf swing. Simultaneously, Acc_X can reveals the occurrence of "impact" moments: impacts are often accompanied by a dramatic change in acceleration in the x-direction. The combined analysis of these two parameters allows for a more comprehensive detection of swing dynamics.

Figure 3.10 exhibit distinctive patterns corresponding to each key phase of Euler_Z and Acc_X over time.

- Set-Up: Relatively stable Euler_Z and Acc_X values
- Top of the Backswing: Significant decrease in Euler_Z, indicating maximum rotation away from the target
- Impact: Rapid increase in Euler_Z as the club accelerates through the ball, coinciding with a sharp positive spike in Acc_X
- Follow Through: Peak Euler_Z value, reflecting full rotation past the impact point, while Acc_X shows a rapid deceleration
- Finish: Gradual decline and stabilization of both Euler_Z and Acc_X

With an understanding of these patterns, it was possible to devise an algorithm for the automatic detection and segmentation of key phases of the golf swing. The swing detection algorithm was implemented in Python, leveraging data analysis libraries such as pandas and numpy, along with visualization tools from matplotlib. The flow of the detection algorithm is shown in Figure 3.11:

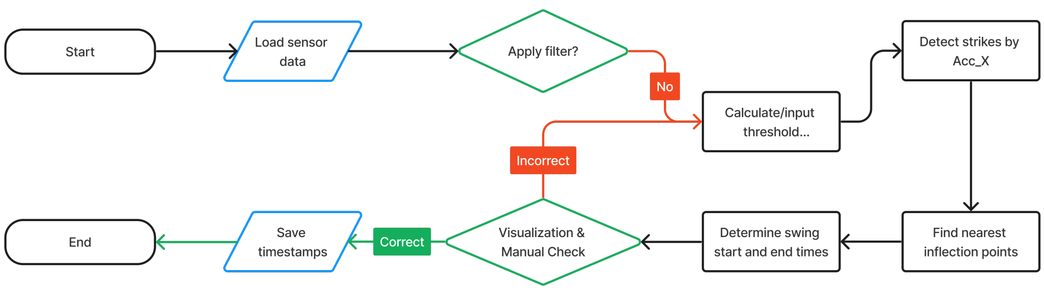


Figure 3.11: The full flow of the swing detection algorithm

The algorithm consists of several key steps:

Data Preprocessing: The raw sensor data, typically stored in CSV format, is first loaded into a pandas DataFrame for easier manipulation and analysis. To ensure the data is clean and reliable, a low-pass Butterworth filter is applied to smooth the data. Specifically, this filter is used to process the Euler angles and acceleration measurements, which are prone to high-frequency noise. The Butterworth filter is chosen for its maximally flat frequency response in the passband, which helps preserve the genuine motion characteristics of the data while effectively attenuating unwanted noise.

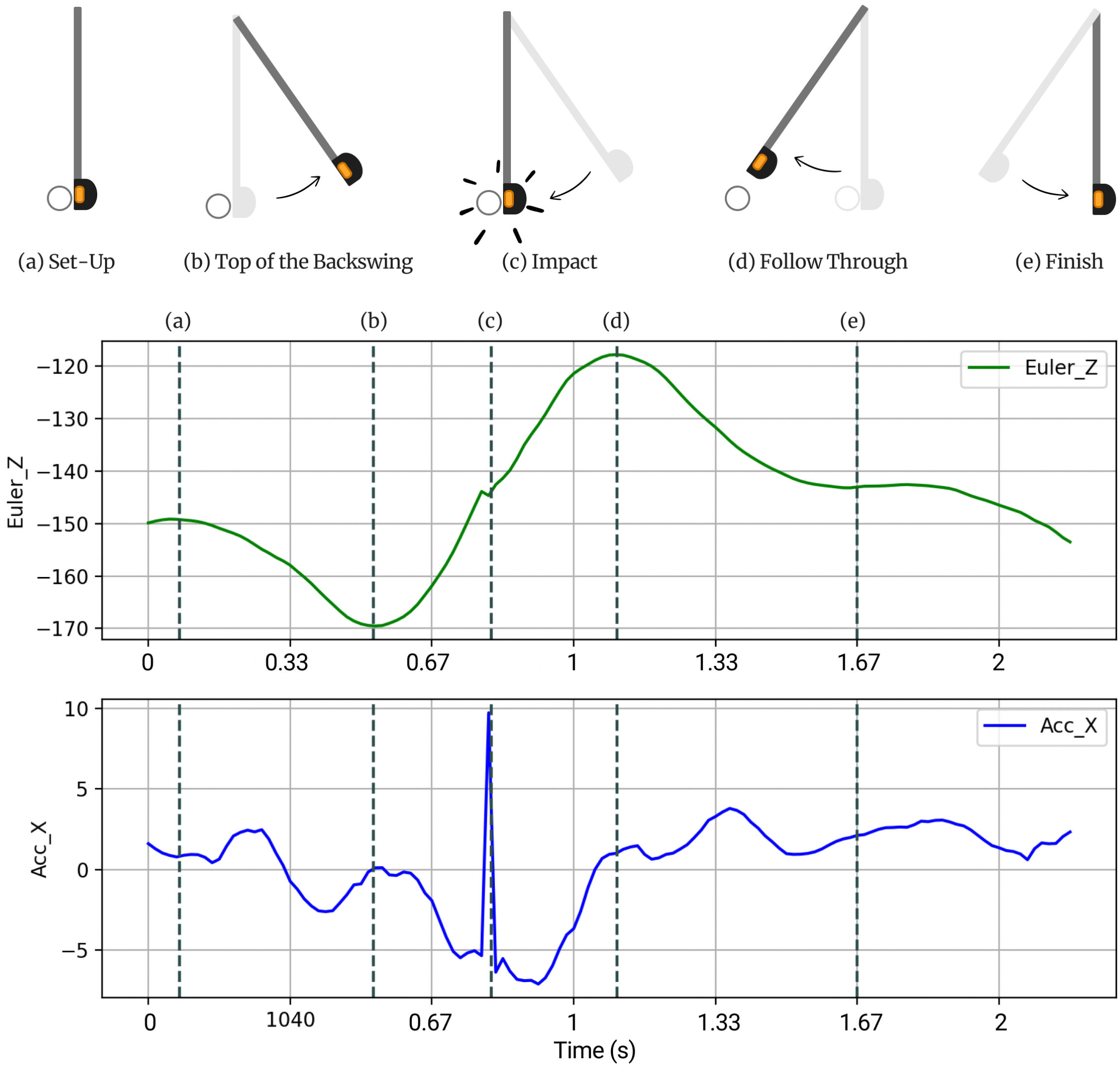


Figure 3.10: An example of golf swing phase and corresponding sensor data. The top panel illustrates key swing moments: (a) Set-Up, (b) Top of the Backswing, (c) Impact, (d) Follow Through, and (e) Finish. The middle panel shows the Euler_Z angle progression, while the bottom panel displays the Acc_X values over time. Vertical dashed lines align the key moments to their respective patterns in both Euler_Z and Acc_X, demonstrating how changes in these parameters reflect the dynamics of a golf swing.

For preprocessing step, a 2nd-order Butterworth filter with a cutoff frequency of 3 Hz is employed. This cut-off frequency was chosen based on the dynamic range of swing motion in several tests prior to the experiment. The application of this filter can improves the accuracy of subsequent motion detection and analysis by removing spurious noise without distorting the essential signal features.

Threshold Calculation: A dynamic thresholding approach is employed to detect ball strikes. The algorithm iteratively adjusts the threshold value to identify the desired number of strikes. It calculates the difference in acceleration along the Z-axis (acc_diff) and considers peaks above the threshold as potential strikes. The threshold is fine-tuned until the target number of strikes is detected or until the algorithm determines that the desired number of strikes cannot be reliably identified.

Strike Detection: Using the calculated threshold, the algorithm identifies indices in the sensor data where the absolute difference in Z-axis acceleration exceeds the threshold. To prevent false positives, it ignores strikes too close to the start of the data series and ensures a minimum time interval between consecutive strikes.

Swing Segmentation: For each detected strike, the algorithm identifies the start and end of the corresponding swing. This is achieved by finding the nearest inflection points in the Euler Z angle before and after the strike. The second derivative of Euler Z is calculated to identify these inflection points, which typically correspond to the transition between swing phases. At the end, the detected batting indices and swing start/end times will be stored as timestamp files in CSV format for use in further analysis.

Manual Inspection The algorithm generates a comprehensive visualization of the detected swing, allowing for manual inspection and error correction. The generated graphs include:

- Acceleration data for all three axes
- Detected strike points
- Highlighted swing regions
- Euler Z angle progression

If the automatic detection is not satisfactory, the desired number of strikes and threshold can be manually entered to more accurately find the swing cycle.

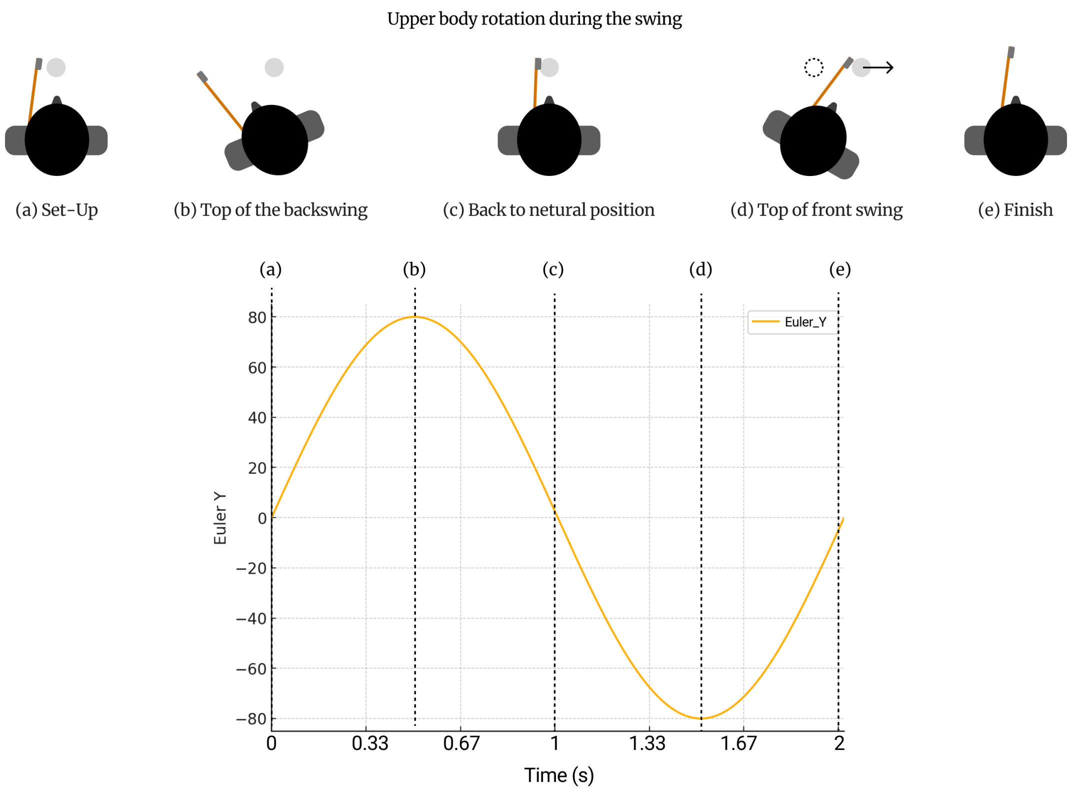


Figure 3.12: An example of golf swing phase and corresponding sensor data. The top panel illustrates key moments of upper body movement during a swing: (a) Set-Up, (b) Top of the backswing, (c) Back to netural position, (d) Top of front swing, and (e) Finish. The bottom panel displays the Euler_Y values over time.

Upper-Body Movement Analysis

The sternum sensor provides Euler_Y data for analyzing upper body rotation. The change in rotation between the start and end of the swing is normalized for each swing and this result is visualized in order to observe the dynamic characteristics of the upper body between groups.

To provide a clear comparative analysis, the algorithm fits a polynomial curve to the data points using weighted curve fitting. Polynomial fitting offers a significant advantage over simple averaging for analyzing upper-body rotation data, particularly by ensuring that all fitted curves start from a consistent initial value, typically zero. This alignment is crucial for accurate comparative analysis, as it eliminates initial discrepancies that can obscure true differences in movement dynamics. Weighted polynomial fitting allows the initial data points to be emphasized, ensuring a consistent baseline for all groups and facilitating clear visual and statistical comparisons.

This process involves defining a polynomial function, $P(x) = ax^4 + bx^3 + cx^2 + dx$, which models the upper-body rotation data. The weighted curve fitting method assigns greater importance to the initial data points by using an exponential weighting function, $w_i = \exp\left(-\frac{x_i}{x_{\text{max}}}\right)$, where x_i represents each data point and x_{max} is the maximum value of x. This weighting ensures that the fitted polynomial starts from a consistent initial value, typically zero. The curve fitting is performed by minimizes the weighted least squares error between the observed data and the polynomial model. The fitting process yields the optimal polynomial coefficients $a, b, c,$ and d and their covariance matrix, providing a robust and accurate representation of the data.

The fitted curve is then plotted for each group in distinct colors. The 95% confidence intervals for the polynomial fit are calculated and plotted through following process: Initially, a weighted least squares method fits the polynomial to the data, emphasizing earlier points. A smooth curve is generated by evaluating the polynomial at 1000 evenly spaced points between 0 and 1. Degrees of freedom (dof) are computed as the difference between the number of data points (`n`) and the number of polynomial parameters (`p`). The standard error of the fit (`sigma`) is derived from the residuals. The standard error of the prediction for each point on the smooth curve is calculated, and these errors, scaled by the appropriate t-value from the t-distribution, yield the 95% confidence intervals.

Chapter 4

Results

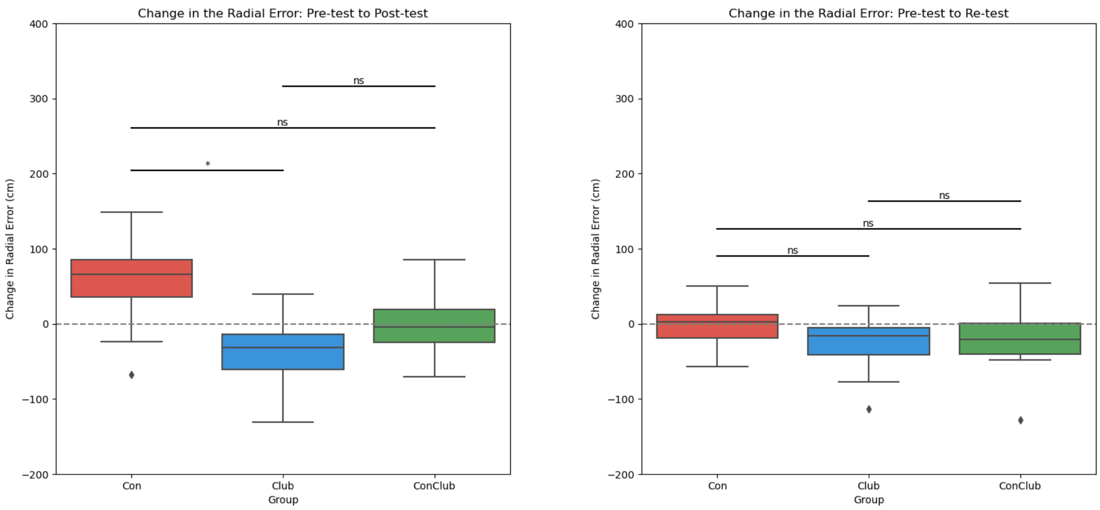
This chapter presents the key findings of our study investigating the effects of controller fidelity on motor learning in a VR golf putting task. We focused on performance outcomes (radial error, initial release angle, ball travel distance) and kinematic data (sternum rotation). Detailed results and statistical tests are provided in the appendices.

4.1 Performance Outcome Variables

Contrary to our hypotheses, we found no significant differences in performance improvement between the VR training groups (Con and ConClub) and the real-world training group (Club). Neither VR condition led to significant improvements in radial error, initial release angle, or ball travel distance compared to real-world practice.

4.1.1 Radial Error R

Radial Error is the absolute difference between the ball's final position and the center of the hole. A repeated-measures ANOVA revealed a marginally significant main effect of test phase for the Club group ($F(2, 14) = 3.187$, $p = 0.072$), but no significant effects for the Con or ConClub groups, as shown in 4.1. Post-hoc tests for the Club group showed a marginally significant improvement from pre-test to post-test ($p = 0.087$) followed by a significant decline from post-test to retention test ($p = 0.044$). This suggests a potential short-term learning effect that did not persist. Although a one-way ANOVA revealed a significant main effect of group for the pre-post change in radial error ($F(2, 21) = 5.217$, $p = 0.014$), post-hoc tests only revealed a significant difference between the Club and Con groups ($p=0.011$), with Club showing greater improvement. This between-group difference was not maintained for the pre-retention change, which showed no significant effect of group. The detailed results and analysis are shown in Appendix A.1.



(a) Pre-test to Post-test

(b) Pre-test to Retention-test

Figure 4.1: Change in the Radial Error Between Test
Values less than 0 indicate an improvement. The smaller the value, the greater the performance improvement, and vice versa. ***** means *significant*; **ns** means *not significant*

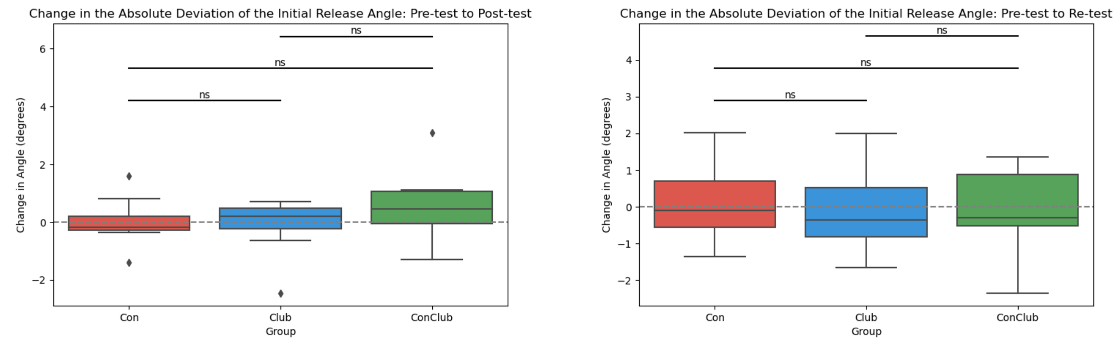
4.1.2 Initial Release Angle and Ball Travel Distance

The initial release angle and ball travel distance, representing aiming consistency and force control respectively, showed no significant changes within any of the three groups across testing phases. Figures 4.2 visually represent the changes of the Initial Release Angle using boxplots, while Figures 4.3 depict the changes in ball travel distance in a similar manner.. Similarly, the between-group comparisons for these measures revealed no significant effects (see Appendix A.2 and A.3 for detail).

4.2 Kinematic Analysis: Sternum Rotation

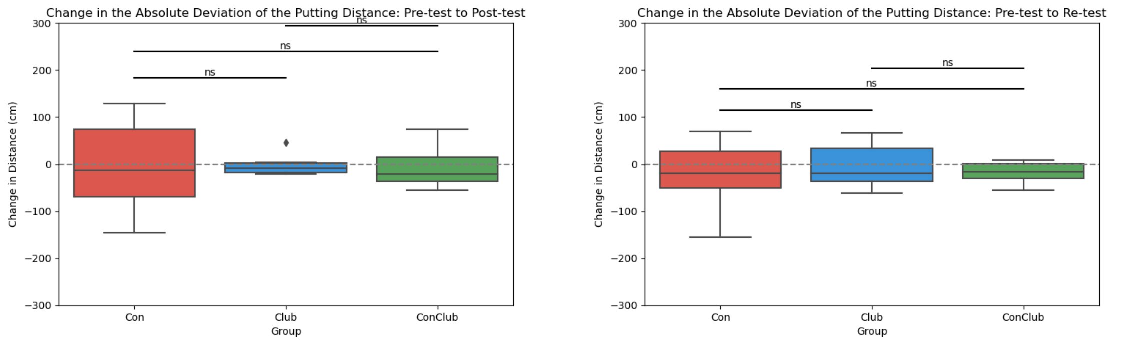
Figures 4.4 through 4.6 illustrate the quadratic polynomial fits of sternal rotational trajectories for each group across the three tests. Figures B.1 through B.3 in Appendix B.2 show quadratic polynomial fits and their 95% confidence intervals for the sternal rotation trajectories of the three groups in each test. Refer to Table B.1 for comprehensive statistics, including mean and standard deviation across all test phases and groups.

The kinematic analysis of sternum rotation revealed more nuanced differences between groups. The Club group demonstrated reduced oscillation amplitude and



(a) Pre-test to Post-test *(b)* Pre-test to Retention-test

Figure 4.2: Change in the Absolute Deviation of the Initial Release Angle
Values less than 0 indicate an improvement, and vice versa.
ns: *not significant*



(a) Pre-test to Post-test *(b)* Pre-test to Retention-test

Figure 4.3: Change in the Absolute Deviation of the Putting Distance
Values less than 0 indicate an improvement, and vice versa.
ns: *not significant*

variability after training, suggesting improved motor control. Figure 4.4 showing changes in Euler angles for Club across test phases. The Con group, however, showed increased variability in sternum rotation after VR training. Figure 4.5 showing changes in Euler angles for Con across test phases].

4.2.1 ConClub Kinematics

The ConClub group exhibited the most distinct kinematic pattern. While showing a decrease in oscillation amplitude similar to the Club group, the ConClub group also exhibited a forward shift in the timing of peak rotation in the post-test. [Figure 4.6 showing changes in Euler angles for ConClub across test phases]. This unique pattern may be attributed to the higher fidelity haptic feedback provided by

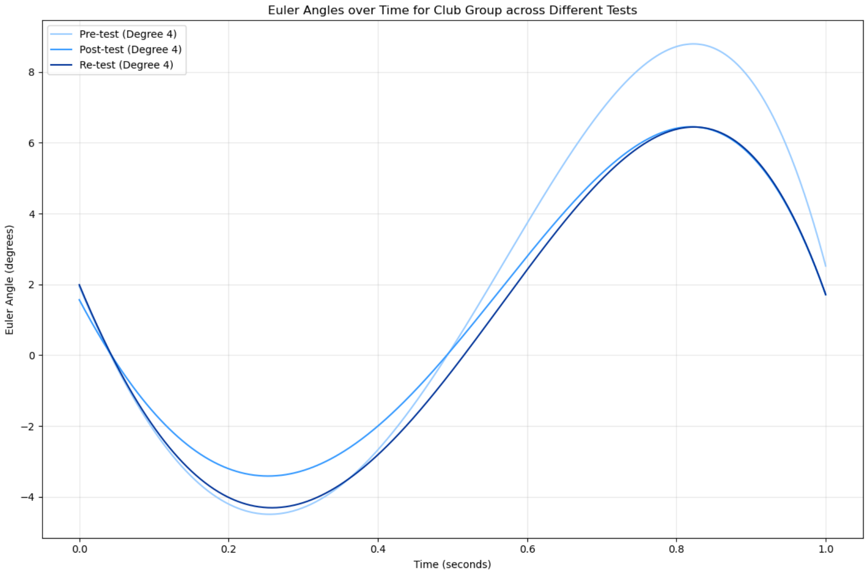


Figure 4.4: Changes in Euler Angles Over Time for the Club Group Across Pre-test, Post-test, and Re-test Phases

the real putter in VR and warrants further investigation. Detailed kinematic data and statistical analysis can be found in Appendix B.1 and B.2.

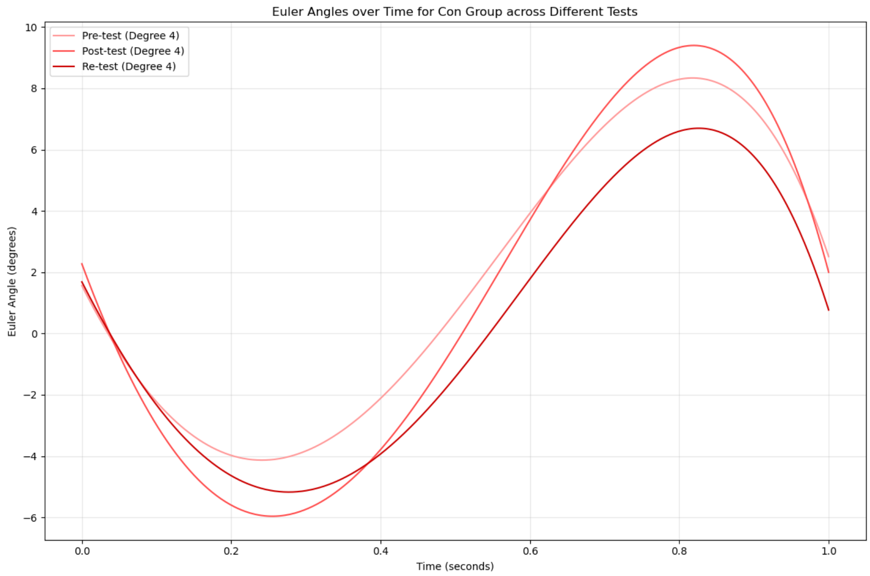


Figure 4.5: Changes in Euler Angles Over Time for the Con Group Across Pre-test, Post-test, and Re-test Phases

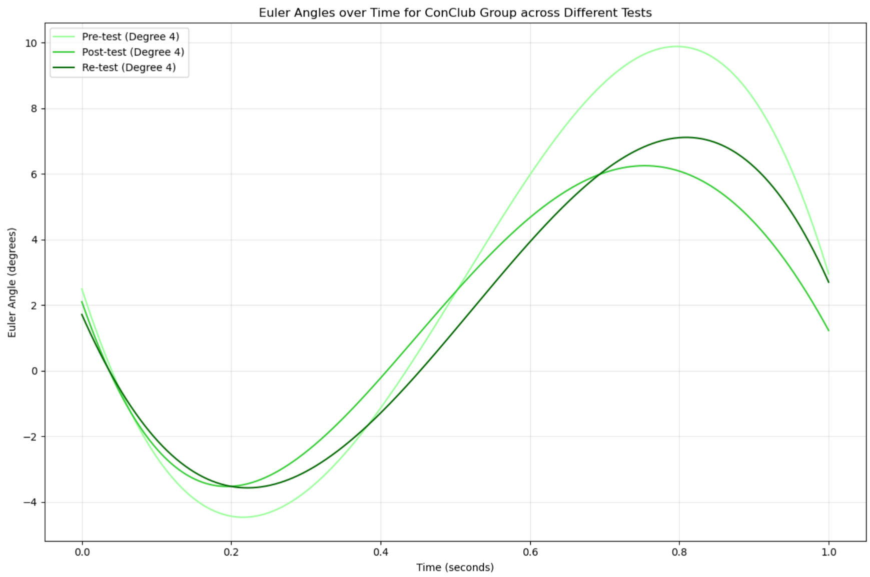


Figure 4.6: Changes in Euler Angles Over Time for the ConClub Group Across Pre-test, Post-test, and Re-test Phases

Chapter 5

Discussions

5.1 Performance results discussion

This study aimed to investigate the effects of real-world objects in a VR training environment on motor learning performance and kinematic characteristics in a golf putting task. While previous research has explored the impact of VR interventions with varying degrees of fidelity on motor learning, most studies have focused solely on the physical fidelity of the VR program. A limited number of studies have examined the effects of controller weight on motor learning performance, but they have not considered the influence of controller shape and mode of operation. Additionally, when measuring the effect of VR training on ball sport learning performance, most studies have relied on performance metrics (e.g., error distance to the target) without considering component metrics (e.g., launch angle) that contain more detailed information, limiting the interpretability of their conclusions [50].

The current study hypothesized (H1) that a high-fidelity controller replicating *real golf putter* would result in better VR motor learning compared to a simple low-fidelity controller, although neither would be as effective as practicing with *real golf putter* in a real environment. The analysis of indirect motion metrics (radial error) did not support this hypothesis. The Club group showed a near-significant decrease in radial error from pre-test to post-test, followed by a significant increase from post-test to retention-test. In contrast, the Con and ConClub groups did not exhibit any statistically significant changes. However, the Club group showed significantly greater error reduction between the pre-test and post-test compared to the ConClub group, suggesting that both VR interventions were less effective in improving putting performance than realistic training, regardless of controller fidelity.

In the Con group, most feedback centered around the controllers being too light to simulate the weight of the clubs, which significantly detracted from the experience. In contrast, participants in the ConClub group, using real weighted putters, reported a lack of sufficient impact. One participant noted, "It helped, but not that much.

Because the swing is very inaccurate, it sometimes feels like I'm just gliding over the ball instead of hitting it" (D.1). While the ConClub putter has weight and shape, the VR system doesn't provide feedback of impact with the ball. This is the key sensory element that's missing. This suggests that in a VR golf environment, the perceived need for weight may outweigh the importance of impact sensation.

Interestingly, the analysis of direct motion metrics, such as Initial Release Angle and ball travel distance, showed no statistically significant changes across the testing phases. Even the Club group, which showed near-significant fluctuations in radial error, did not exhibit significant changes in these metrics. The Initial Release Angle reflects the level of aiming skill, which we believe is closely related to the skills of Visual Search Behavior (VSB). In static skills (e.g., golf putting, shooting), the Quiet Eye Duration (QED) is usually the primary focus of VSB. Longer QED is usually associated with better performance in targeted skills such as shooting, golf putting, and dart throwing [65]. Harris et al. found that for novices, short-term putting drills (either VR or reality) do not seem to significantly affect QED, which may be due to the fact that quiet eye is an advanced visual control strategy that may require longer training to develop [50]. This reflects the fact that QEDs are more difficult to improve, which can explain why we did not observe a change in Initial Release Angle.

A participant from the Con group highlighted the limitations of VR training for tasks involving physical weight and distance, noting that while it is effective for aiming and angle control, it falls short in accurately training distance perception, such as judging how far the ball will travel. Another participant emphasized the difficulty of judging distances in VR, indicating the need to rely on trial and error. These observations support the finding that VR training may be more effective for improving aiming skills than for enhancing distance control (D.1).

Deviation of the ball's travel distance reflects the power control ability, which consists of estimating the distance to the target with the eyes and controlling the muscle force. Therefore, compared to aiming, power control is more complex and is typical of visuomotor coordination behavior [66]. Estimating the distance is a perceptual-cognitive skill, which involves visual search and spatial perception [67], while controlling the muscle force is directly related to body awareness [68]. Despite evidence that VR training can affect users' perception of their own body position and movement [69], no significant progress or regression was observed in any of the three groups in our results. This may reflect the fact that putting power control is a more complex skill involving the interaction of visuospatial ability (VSA) and body awareness, where changes in one are likely to affect the other and may not be sufficient to have an overall effect. The relationship between VSA and body awareness in VR environments requires further study, particularly in the context of complex motor skills like golf putting.

A participant from the ConClub group pointed out the challenge of body alignment in VR, noting that you can see the virtual environment but not your own body, which can create a disconnect. This lack of body awareness in VR could contribute to the difficulty in improving power control skills (D.1)..

Several factors may have contributed to the limited observed changes in motor performance:

Task difficulty The 6m distance between the starting point and the target in the experiment is considered to be a relatively long distance to putt. In real-world motor training, novice learners may benefit more from simpler tasks that help them understand the basic movement mechanisms [43]. The effect of task difficulty on motor learning in VR environments may be a result of the mental workload during the task [70]. Harris et al. found that in golf putting, the perceived distances for real and virtual reality putts were similar, implying that the distances we set in VR and real world gave participants a similar amount of perceived mental workload [71]. That is, since we pre-set a same difficulty for every participant, they may feel bored or frustrated when practicing [8], which increases their mental workload and thus reduces the effectiveness of motor learning.

Skill transfer We can speculate that motor learning in VR may have occurred, but that this change was not transferred to the real-world. Harris et al. found that practicing in a VR environment brought about higher perceptual stress compared to golf putting practice in the real-world. Higher perceptual stress means that users may be distracted or have difficulty concentrating in a virtual reality environment, which may affect the transfer of skills from VR to the real-world [50]. However, since we did not directly test the learning effect in the VR environment, and the Post-test in the experiment actually measured the effect after transferring to the real world, we don't know whether the skill was not acquired at all during the VR training, or whether the skill was acquired but no effective transfer was achieved.

Training strategies Ericsson et al. found that the best environments for learning motor skills are well-organized, with activities specifically designed to enhance particular abilities [72]. Thus, tasks that are well structured are more conducive to skill learning than simple play (without goals or external instructions) [34]. For our study, video-mediated five-minute instruction for complete novices may have been very limited to induce significant learning effects.

Sample size The limited number of participants in each group (n = 8) could have contributed to the lack of statistically significant differences observed in performance outcomes and kinematic variables. As noted by Button et al., small sample sizes can lead to underpowered studies, reducing the likelihood of detecting true effects and increasing the risk of Type II errors [73].

The high variability in the data and the lack of significant differences within and between groups for these metrics (Tables 4.8, 4.10, 4.11, 4.13, 4.15, and 4.16) suggest that the sample size may not have been sufficient. For example, the one-way ANOVA results for pre-post angle difference (Table 4.10) and pre-retention angle difference (Table 4.11) yielded F-statistics of 0.888 and 0.056, respectively, with p-values well above the conventional 0.05 threshold. Similarly, for ball travel distance, the one-way ANOVA results for pre-post difference (Table 4.15) and pre-retention difference (Table 4.16) showed F-statistics of 0.021 and 0.150, respectively, with p-values far exceeding 0.05. These findings indicate that the sample size may have been insufficient to detect meaningful differences in Initial Release Angle and ball travel distance.

5.2 Kinematic results discussion

The current study also hypothesized (H2) that the kinematic characteristics of participants during test trials in real environments, after practicing with high-fidelity VR controllers, will not differ significantly from those who practiced with *real golf putter* . Our findings do not support this hypothesis.

The sternum serves as the center of the upper body, and its rotation reflects the overall rotation of the upper body during the golf swing. We found that the **Club** group, which trained in the real-world, demonstrated more conservative and convergent upper body rotation patterns after training. There was a decrease in both the maximum reverse rotation angle reached during backswing and the maximum forward rotation angle reached during follow-through. Additionally, the standard deviation decreased from pre-test (M = 1.66, SD = 5.92) to post-test (M = 1.19, SD = 4.25), indicating that the kinematic patterns stabilized after training. These changes in motor characteristics likely reflect improved visuomotor skills. Previous research has shown that upper body rotational consistency, particularly in shoulder alignment and trunk rotation, is a hallmark of high-level golfers [74], [75]. Reduced shoulder rotational variability may indicate better ball striking ability [74], and forearm variability correlates with horizontal launch angle consistency [75].

In contrast, the **Con** group using the standard VR controller exhibited more exaggerated upper limb rotation patterns after training. The standard deviation increased from pre-test (M = 1.71, SD = 6.48) to post-test (M = 1.25, SD = 7.28), suggesting that VR training may have disrupted the acquisition of consistent kinematic patterns. This finding aligns with Brock et al.'s study [59], which found that real and virtual putters elicited significant differences in postural control, with the VR environment characterized by larger, more consciously controlled movements. They attribute these differences to the lack of haptic feedback in VR. Furthermore, research has shown that kinematic patterns learned in VR can transfer to real-world tasks [3], [11], [19], potentially explaining the increased motion amplitude observed in the Con group's real-world post-tests. However, due to the lack of significant differences in radial error, we could not determine whether these altered kinematic patterns negatively impacted performance.

The *ConClub* group exhibited distinct kinematic characteristics. During VR training, they showed a similar pattern of decreased amplitude and variance as the Club group, suggesting that high-fidelity VR controllers can mitigate the exaggerated kinematic patterns typically seen with standard VR controllers. This allows the acquired kinematic patterns to more closely resemble those of the Club group trained in the real-world. Intriguingly, the ConClub group's post-test results revealed a more pronounced phase shift not observed in the other groups. The timing of maximum positive sternal rotation appeared to shift forward, corresponding to the end of the follow-through phase after ball impact.

We hypothesize that the unique kinematic patterns observed in the ConClub group may be attributed to the enhanced haptic feedback provided by the high-fidelity VR controller. Research has shown that haptic feedback plays a crucial role in motor learning and control [36], [76]. The realistic inertia and weight distribution of the ConClub likely facilitated the development of a more efficient and precise swing pattern. This is supported by studies demonstrating the benefits of haptic guidance in motor skill acquisition [77].

In the post-test, the pattern exhibited a more pronounced phase shift, a phenomenon that was not observed in either of the other two groups. As there is no existing research explaining this phenomenon, we speculate that it may be caused by the absence of the impact sensation when the ball strikes the club in a VR environment using ConClub. In actual putting, the moment of impact signifies the ball's contact with the club, marking the transition from the forward swing phase to the follow-through phase. Essentially, this touch event occurs at the midpoint of the swing, serving as a crucial temporal marker. When participants sense this point in their swing, they may subconsciously adjust their rhythm in each phase to optimize energy efficiency. However, in the ConClub group, the absence of impact sensation meant that participants could only perceive the moment of ball contact through visual feedback. Although the ConClub closely resembled a real putter, the lack of impact feedback meant that swing tempo was regulated solely by the visual cues provided in VR, without the tactile feedback of impact vibration. This mismatch between visual and tactile information ultimately led to the development of unique kinematic patterns in the participants. In the Con group, although there was no impact sensation as in the ConClub group, this specific kinematic pattern associated with real putter did not develop during VR training because the conventional controllers were significantly different in operation, quality, and shape compared to real putter. Further research is needed to validate these hypotheses and explore the effects of tactile information mismatches generated by high-fidelity controllers on motor learning.

To summarize, the introduction of real-world golf putter in VR motion training appears to form a kinematic pattern that differs from both standard VR controller training and real-world practice. However, the specific impact of these patterns on overall performance requires further investigation.

It is important to acknowledge the limitations of this kinematic study. The interpretation of sternal rotation magnitude may be influenced by factors such as fatigue resulting from prolonged putting practice, as observed by Evans et al. [78]. Additionally, the small sample size and lack of significant differences in performance metrics limit the generalizability of our findings. Future research should employ larger sample sizes, longer training periods, and more comprehensive performance measures to better understand the effects of high-fidelity VR training on golf putting kinematics and performance.

Chapter 6

Conclusions

This study explored the effects of high-fidelity controllers on motor learning in a virtual reality (VR) golf putting task, comparing both performance and kinematic outcomes across three conditions: real-world practice (Club), VR practice with standard controllers (Con), and VR practice with high-fidelity putters (ConClub). The findings provide important insights into the complex interaction between haptic feedback fidelity and motor skill acquisition in VR environments.

Contrary to our initial hypothesis (**H1**), the results did not indicate a clear performance advantage for high-fidelity VR controllers over standard ones. Neither VR condition (Con or ConClub) demonstrated significant improvements in radial error, initial release angle, or ball travel distance when compared to real-world training. This suggests that performance outcomes in VR may not directly benefit from increased controller fidelity, at least in the short term.

However, kinematic analysis revealed meaningful differences between the groups. Participants in the Club group exhibited more conservative, convergent upper-body rotation patterns post-training, which likely reflects improved visuomotor coordination. On the other hand, those in the Con group displayed exaggerated movements, potentially due to the absence of realistic haptic feedback. Interestingly, the ConClub group displayed a unique blend of kinematic patterns, combining aspects of both real-world and VR-based training. This suggests that while high-fidelity controllers may not immediately enhance performance metrics, they contribute to distinct motor adaptations that bridge the gap between virtual and real-world environments.

The study also identified several challenges inherent to VR-based motor learning, including difficulties in depth and distance perception, the complexity of skill transfer between virtual and real environments, and the need for structured training approaches. Interviews with participants further supported these observations, emphasizing the perceived differences in sensory feedback between VR and real-world contexts.

Our findings on kinematic behavior provide a more nuanced understanding of how high-fidelity controllers influence motor learning. The forward shift in peak rotation timing observed in the ConClub group suggests that high-fidelity haptic feedback may foster unique motor adaptations that do not mirror those of real-world training (rejecting **H2**). While these kinematic changes did not directly translate into performance improvements, they highlight the potential for high-fidelity controllers to shape learning processes in VR in ways that warrant further exploration.

These insights contribute to the growing body of knowledge on motor learning in virtual environments and underscore the need for continued research. Future studies should focus on refining VR haptic feedback systems, improving training protocols, and exploring the long-term effects of VR on skill acquisition and transfer to real-world performance. As VR technology advances, optimizing these systems will be critical for maximizing the effectiveness of VR-based motor learning.

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Appendix A

Performance data

A.1 Radial Error

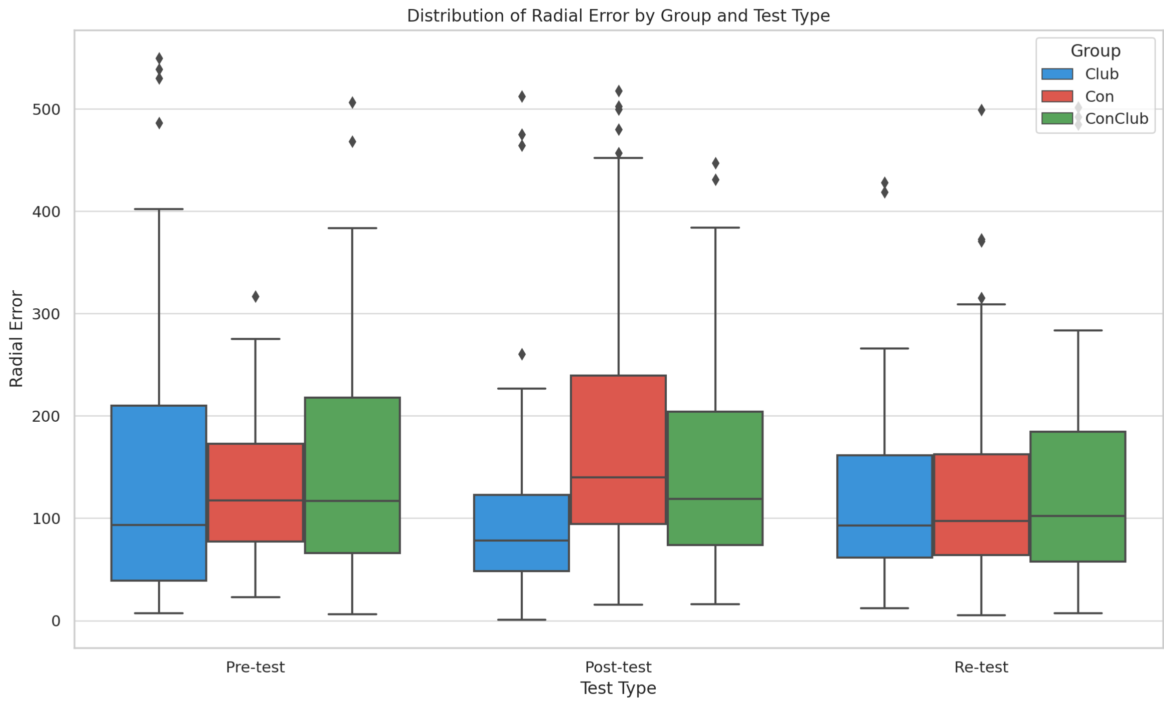

Figure A.1: Distribution of Radial Error by Group and Test Type. Boxplots show the Radial Error distributions across different test types (Pre-test, Post-test, Re-test) for each group (Club, Con, ConClub). The color scheme distinguishes between the groups: Club (blue), Con (red), and ConClub (green).

Group	Test Phase	Radial Error	Standard Deviation
Club	Pre-test	115.425	101.056
Club	Post-test	94.263	81.933
Club	Re-test	111.971	80.535
Con	Pre-test	123.810	93.347
Con	Post-test	139.480	118.175
Con	Re-test	125.682	93.235
ConClub	Pre-test	153.676	111.103
ConClub	Post-test	149.281	105.815
ConClub	Re-test	144.383	102.518

Table A.1: Radial Error and Standard Deviation by Group and Test Phase

Before conducting the analysis, we assessed the assumptions of homogeneity of variance and normality. Residual plots (Figure C.2) for both the Pre-Post Difference and Pre-Re Difference showed that residuals were randomly scattered around the zero line, suggesting linearity. While there were slight indications of heteroscedasticity, this was considered minimal and unlikely to significantly impact the results. Q-Q plots (Figure C.1) and histograms (Figure C.3) further supported the normality assumption, showing that the residuals for both predictors lie approximately along the 45-degree line and display approximately bell-shaped distributions.

Comparison with-in Group A repeated measures analysis of variance (ANOVA) was conducted to examine the effects of test type (pre-test, post-test, and re-test) on radial error across three experimental groups: Con, Club, and ConClub (as shown in Table A.2). Mauchly's test confirmed that the assumption of sphericity was met for all groups (p ¿ 0.05), thus no corrections were applied to the degrees of freedom.

The ANOVA results revealed no significant main effect of test type for the Con group (F(2, 14) = 0.412, p = 0.670, partial η^2 = 0.038) or the ConClub group (F(2, 14) = 0.204, p = 0.818, partial η^2 = 0.011). However, a marginally significant main effect was observed for the Club group (F(2, 14) = 3.187, p = 0.072, partial η^2 = 0.084). These partial η^2 values indicate small to medium effect sizes, suggesting that test type accounted for 3.8%, 8.4%, and 1.1% of the variance in radial error for the Con, Club, and ConClub groups, respectively.

Given the marginally significant result for the Club group, post-hoc paired t-tests were conducted (as shown in Table A.3). These analyses revealed a marginally significant difference between post-test and pre-test performance (t(7) = -1.990, p = 0.087, Hedges' g = -0.229, BF_{10} = 1.265) and a significant difference between post-test and re-test performance (t(7) = -2.456, p = 0.044, Hedges' g = -0.217, BF_{10} = 2.098). No significant difference was found between pre-test and re-test performance (t(7) = 0.392, p = 0.707, Hedges' g = 0.038, BF_{10} = 0.359). The Bayes factors indicate anecdotal evidence for a change from pre-test to post-test, moderate evidence for a change from post-test to re-test, and moderate evidence for no change from pre-test to re-test.

The marginally significant improvement from pre-test to post-test, followed by a significant decline from post-test to re-test, implies a potential short-term benefit of the Club intervention that may not be sustained over time. This pattern is further supported by the Bayesian analysis, which provides a more nuanced interpretation of the evidence for each comparison.

The small to medium effect sizes observed across analyses (partial η^2 ranging from 0.011 to 0.084; Hedges' g ranging from -0.229 to 0.038) suggest that while statistically significant differences were detected, the practical significance of these effects may be limited.

Group	Mauchly's Test		ANOVA Results				
	W	p_{spher}	F	df_1, df_2	p	Partial η^2	ε_{GG}
Con	0.734	0.395	0.412	2, 14	0.670	0.038	0.790
Club	0.808	0.527	3.187	2, 14	0.072†	0.084	0.839
ConClub	0.887	0.697	0.204	2, 14	0.818	0.011	0.898

Table A.2: Repeated Measures ANOVA Results of Radial Error for Test Type Across Groups
W = Mauchly's W; p_{spher} = p-value for sphericity test; F = F-statistic; df = degrees of freedom; p = p-value; η^2 = effect size; ε_{GG} = Greenhouse-Geisser epsilon
$^\dagger p < 0.10$ (marginally significant)

Contrast	t	df	p	Hedges' g	BF$_{10}$	95% CI$_{lower}$	95% CI$_{upper}$
Post-test vs. Pre-test	-1.990	7	0.087†	-0.229	1.265	-0.542	0.084
Post-test vs. Re-test	-2.456	7	0.044*	-0.217	2.098	-0.530	0.096
Pre-test vs. Re-test	0.392	7	0.707	0.038	0.359	-0.275	0.350

Table A.3: Post-hoc Paired t-test Results for Club Group
BF$_{10}$: Bayes Factor in favor of the alternative hypothesis; CI: Confidence Interval for Hedges' g
$^*p < .05$, $^\dagger p < .10$

Comparison between groups The ANOVA for pre-post difference yielded a statistically significant main effect of group (F(2, 21) = 5.217, p = 0.014, η^2 = 0.332)

(Table A.4). This effect size suggests that approximately 33.2% of the variance in pre-post differences can be attributed to group membership.

Post-hoc comparisons using the Tukey HSD test revealed a significant mean difference between the Club and Con groups (MD = 94.9688, p_adj = 0.0111, 95% CI [20.5494, 169.3882]) . The Club group demonstrated superior improvement compared to the Con group. However, the comparisons between Club and ConClub (MD = 39.9435, p_adj = 0.3829) and between Con and ConClub (MD = -55.0253, p_adj = 0.1740) did not reach statistical significance (Table A.4).

The sum of squares for the group effect (SS_group= 36,379.577) relative to the total sum of squares (SS_total = 109,603.738) further corroborates the substantial impact of group allocation on performance improvement.dd

In contrast, the ANOVA for pre-retention differences failed to detect a significant effect of group (F(2, 21) = 0.987, p = 0.387) (Table A.6). The lower F-statistic and higher p-value suggest minimal between-group variability in long-term retention effects. The sum of squares for group (SS_group = 12,745.165) is notably smaller compared to the pre-post analysis, indicating reduced group-based variation in retention scores.

Source	Sum of Squares	df	F	p-value
Group	36,379.577	2	5.217	0.014*
Residual	73,224.161	21	-	-

Table A.4: ANOVA Results for Pre-Post Difference

Group 1	Group 2	Mean Difference	p-adj	Lower	Upper	Reject
Club	Con	94.9688	0.0111	20.5494	169.3882	True
Club	ConClub	39.9435	0.3829	-34.4760	114.3629	False
Con	ConClub	-55.0253	0.1740	-129.4448	19.3941	False

Table A.5: Tukey HSD Post-Hoc Test Results for Pre-Post Difference

Source	Sum of Squares	df	F	p-value
Group	12,745.165	2	0.987	0.387
Residual	53,272.803	21	-	-

Table A.6: ANOVA Results for Pre-Retention Difference

A.2 Initial Release Angle

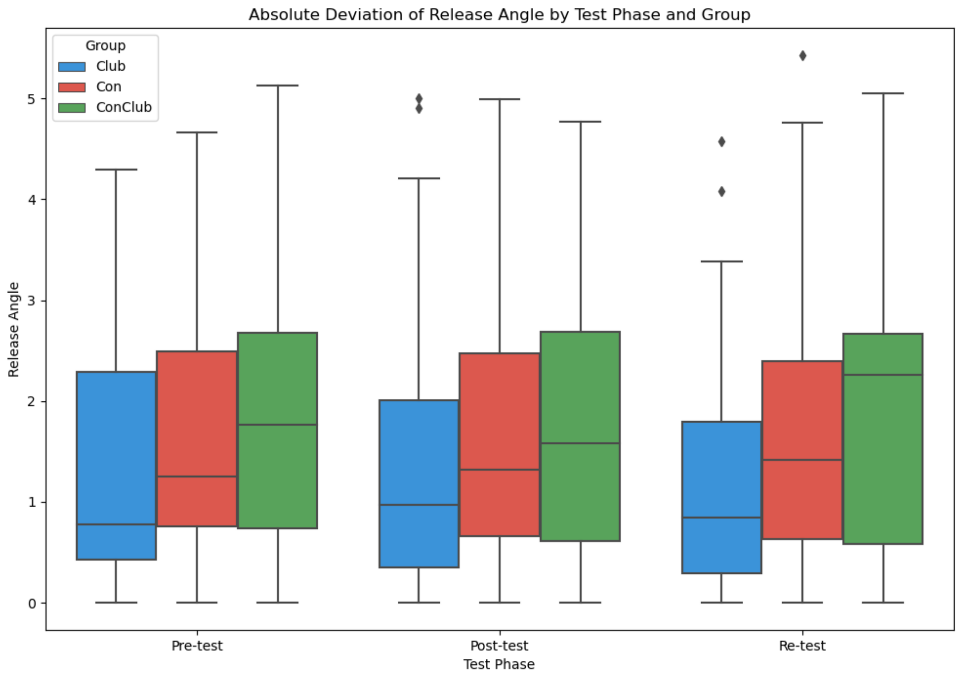

Figure A.2: Absolute Deviation of Initial Release Angle by Group and Difference Test (outliers removed)

In addition to overall accuracy, this subsection analyzes the ball's Initial Release Angle θ during the putting task to assess how different training equipment impact accuracy and consistency in aiming. Table A.7 presents mean Absolute Release Angle and Standard Deviation for each group (Club, Con, ConClub) across Pre-test, Post-test, and Re-test phases. The visualization of the data is shown in Figure A.2 in Appendix A.2.

Before proceeding with the ANOVA, we conducted tests for homogeneity and normality similar to those described for Initial Release Angle. Boxplots showed similar spreads of angle differences across the three groups, with no extreme outliers observed. Q-Q plots displayed points closely following the diagonal line, indicating that the data were approximately normally distributed within each group. Residual plots revealed points randomly scattered around the horizontal zero line, with no discernible patterns, supporting homoscedasticity. These results, detailed in Appendix C, satisfied the assumptions for proceeding with one-way ANOVAs to assess with-in group and between differences in angle values.

Group	Test Phase	Absolute Release Angle (degree)	Standard Deviation
Club	Pre-test	0.958	0.897
Club	Post-test	0.823	0.429
Club	Re-test	0.892	0.846
Con	Pre-test	0.973	0.452
Con	Post-test	0.986	0.737
Con	Re-test	1.066	0.852
ConClub	Pre-test	1.110	0.945
ConClub	Post-test	1.661	1.186
ConClub	Re-test	1.020	0.891

Table A.7: Mean and Standard Deviation of Absolute Release Angle by Group and Test Phase

Comparison with-in Group A one-way repeated measures analysis of variance (ANOVA) was conducted to assess the effect of measurement stage (pre, post, re) on angle measures for each of the three experimental groups: Con, Club, and ConClub. This within-subjects design allowed for the examination of changes in angle measures across three time points within each group. The results are shown in Table A.8.

Mauchly's test indicated that the assumption of sphericity was met for all groups: Con ($W = 0.85$, $p = 0.61$), Club ($W = 0.90$, $p = 0.73$), and ConClub ($W = 0.99$, $p = 0.97$).

For the Con group, the results revealed no statistically significant difference in angle measurements across time points, $F(2, 14) = 0.05$, $p = 0.93$ (Greenhouse-Geisser corrected, $\epsilon = 0.87$), partial $\eta^2 = 0.004$. Similarly, the Club group showed no significant changes over time, $F(2, 14) = 0.07$, $p = 0.92$ (Greenhouse-Geisser corrected, $\epsilon = 0.91$), partial $\eta^2 = 0.006$. The ConClub group also exhibited no significant differences across time points, $F(2, 14) = 1.20$, $p = 0.33$ (Greenhouse-Geisser corrected, $\epsilon = 0.99$), partial $\eta^2 = 0.082$.

The effect sizes, as indicated by partial eta squared values, were small for all groups, with the ConClub group showing a slightly larger, but still non-significant, effect (partial $\eta^2 = 0.082$) compared to the Con (partial $\eta^2 = 0.004$) and Club (partial $\eta^2 = 0.006$) groups.

Comparison between Groups Table A.9 outlines the mean angle differences and standard deviations differences for each group, comparing Pre-test to Post-test and Pre-test to Re-test. Figures 4.2a and 4.2b visually represent these changes using boxplots.

Group	Mauchly's Test		ANOVA Results				
	W	p_{spher}	F	df_1, df_2	p	Partial η^2	ε_{GG}
Con	0.85	0.61	0.05	2, 14	0.93	0.004	0.87
Club	0.90	0.73	0.07	2, 14	0.92	0.006	0.91
ConClub	0.99	0.97	1.20	2, 14	0.33	0.082	0.99

Table A.8: Repeated Measures ANOVA Results for Angle Measurements Across Time
W = Mauchly's W; p_{spher} = p-value for sphericity test; F = F-statistic; df = degrees of freedom; p = p-value; η^2 = effect size; ε_{GG} = Greenhouse-Geisser epsilon.

Group	Comparison	Angle Improvement	Change in Standard Deviation
Club	Pre-Post	-0.135	-0.468
Club	Pre-Retention	-0.066	-0.051
Con	Pre-Post	0.013	0.285
Con	Pre-Retention	0.093	0.400
ConClub	Pre-Post	0.550	0.241
ConClub	Pre-Retention	-0.090	-0.054

Table A.9: The mean angle differences and Change in Standard Deviation by Group and Comparison Phases

The one-way ANOVA has been adapted to analyze the significance of differences of Pre-Post and Pre-Re angle improvements between groups (see Table A.10 and A.11). The (ANOVA for pre-post angle difference yielded the following results: F(2, 21) = 0.888, p = 0.426. The sum of squares attributable to the group effect (SS_group) was 2.109, which constitutes approximately 7.8% of the total sum of squares (SS_total = 27.050). The residual sum of squares ($SS\_residual$) was 24.941, accounting for 92.2% of the total variability.

For the pre-retention angle difference, the ANOVA produced these statistics: F(2, 21) = 0.056, p = 0.946. The group effect sum of squares (SS_group) was 0.151, representing about 0.5% of the total sum of squares (SS_total = 28.441). The residual sum of squares ($SS\_residual$) was 28.290, comprising 99.5% of the total variance.

Comparing the two analyses, the F-statistic for the pre-post difference (F = 0.888) was higher than that of the pre-retention difference (F = 0.056), indicating a relatively larger, though still minimal, between-group variance in the immediate post-test phase. The group sum of squares decreased from 2.109 in the pre-post analysis to 0.151 in the pre-retention analysis, suggesting a reduction in group-based differences over time.

The total sum of squares increased slightly from 27.050 in the pre-post analysis to 28.441 in the pre-retention analysis, potentially reflecting a small increase in overall variability of angle differences during the retention period.

Source	Sum of Squares	df	F	p-value
Group	2.109	2	0.888	0.426
Residual	24.941	21		

Table A.10: ANOVA results for Pre-Post Angle Difference

Source	Sum of Squares	df	F	p-value
Group	0.151	2	0.056	0.946
Residual	28.290	21		

Table A.11: ANOVA results for Pre-Retention Angle Difference

A.3 Ball's Travel Distance

A.3.1 Ball's Travel Distance D

This subsection analyzes the ball's travel distance during the putting task to assess how different training equipment impact accuracy and consistency in force control. The absolute deviation in ball's travel distance was examined across three groups (Club, Con, and ConClub) over three test phases (Pre-test, Post-test, and Re-test). Figure A.3 in Appendix A.3 presents boxplots illustrating the distribution of absolute deviations for each group and test phase. The results are shown in Table A.12.

Before proceeding with the ANOVA, we conducted tests for homogeneity and normality similar to those described for Ball's Travel Distance. Preliminary analyses of angle and its differences values met ANOVA assumptions. Boxplots revealed comparable distributions across groups without extreme outliers. Q-Q plots demonstrated approximate normality within each group, with points adhering closely to the diagonal. Residual plots exhibited random scatter around the zero line, supporting homoscedasticity. These findings, detailed in Appendix C.0.3, confirmed the suitability of one-way ANOVAs for assessing within-group and between-group differences in angle values.

Comparison with-in Group One-way repeated measures ANOVAs were conducted to examine the effects of time on distance measurements for three groups: Con,

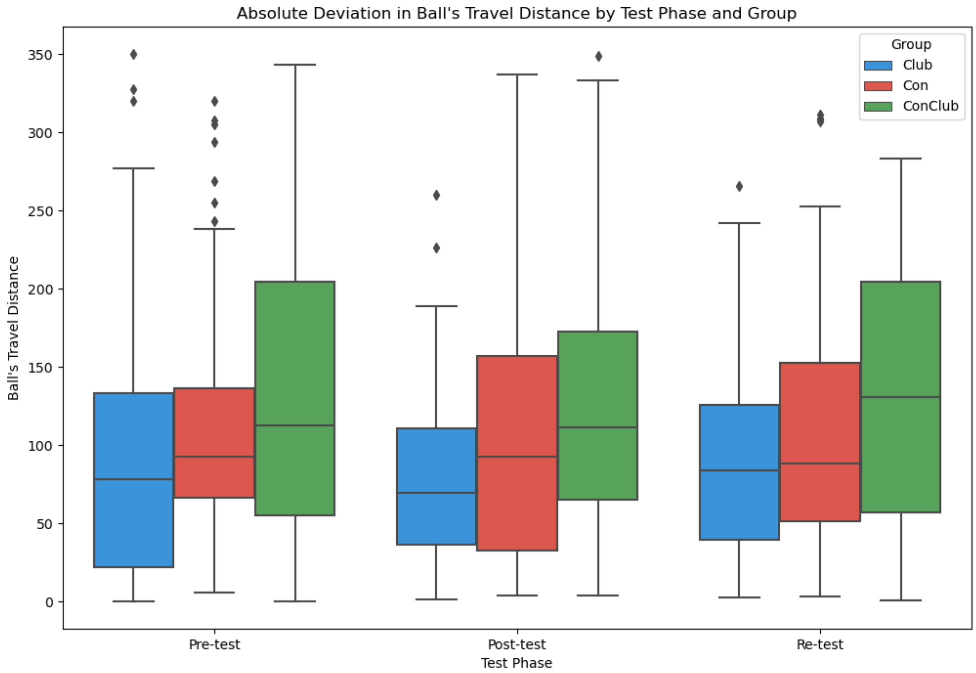

Figure A.3: Absolute Deviation of Ball's Travel Distance by Group and Difference Test

Club, and ConClub, the results are shown in Table A.13. Prior to analysis, Mauchly's test of sphericity was performed for each group. The assumption of sphericity was met for all groups: Con group (W = 0.778, p = 0.471), Club group (W = 0.502, p = 0.126), and ConClub group (W = 0.553, p = 0.169). Despite meeting the sphericity assumption, Greenhouse-Geisser corrections were applied to ensure robustness of the analysis, given the relatively small sample sizes.

The repeated measures ANOVA for the Con group yielded no statistically significant effect of time on angle measurements, F(2, 14) = 0.303, p = 0.702 ((Greenhouse-Geisser corrected, ϵ = 0.82), partial η^2 = 0.032. For the Club group, no significant effect of time was observed, F(2, 14) = 0.099, p = 0.829 (Greenhouse-Geisser corrected, ϵ = 0.667), partial η^2 = 0.007. The ConClub group also showed no significant effect of time, F(2, 14) = 0.889, p = 0.404 ((Greenhouse-Geisser corrected, ϵ = 0.69), partial η^2 = 0.016.

Although all effects were non-significant, there were notable differences in effect sizes across groups. The Con group demonstrated the largest effect size (partial η^2 = 0.032), which can be interpreted as a small to medium effect. This was followed by the ConClub group (partial η^2 = 0.016), showing a small effect, and the Club group (partial η^2 = 0.007), indicating a very small effect.

Group	Test Phase	Absolute Distance Deviation (cm)	Standard Deviation
Club	Pre-test	39.694	29.987
Club	Post-test	36.875	28.426
Club	Re-test	33.532	36.209
Con	Pre-test	62.931	63.973
Con	Post-test	61.240	57.176
Con	Re-test	43.233	28.208
ConClub	Pre-test	69.057	61.083
ConClub	Post-test	61.363	46.647
ConClub	Re-test	52.196	65.313

Table A.12: Mean and Standard Deviation of Absolute Distance Deviation by Group and Test Phase

Group	Mauchly's Test		ANOVA Results				
	W	p_{spher}	F	df_1, df_2	p	Partial η^2	ε_{GG}
Con	0.78	0.47	0.30	2, 14	0.70	0.032	0.82
Club	0.50	0.13	0.10	2, 14	0.83	0.007	0.67
ConClub	0.55	0.17	0.89	2, 14	0.40	0.016	0.69

Table A.13: Repeated Measures ANOVA Results for Distance Measurements Across Time
W = Mauchly's W; p_{spher} = p-value for sphericity test; F = F-statistic; df = degrees of freedom; p = p-value; η^2 = effect size; ε_{GG} = Greenhouse-Geisser epsilon.

Comparison between Groups Table A.14 provides insight into the distance improvement between test phases. Figures 4.3a and 4.3b visually represent these changes using boxplots. The "ns" annotation above the boxplots indicates that the differences between groups were not statistically significant (from the ANOVA that follows).

The one-way ANOVA has been adapted to analyze the significance of differences of Pre-Post and Pre-Re distance improvements between groups (as shown in Table A.15 and Table A.16). The ANOVA for pre-post distance difference yielded the following results: F(2, 21) = 0.021, p = 0.979. The sum of squares attributable to the group effect (SS_group) was 162.862, which constitutes approximately 0.2% of the total sum of squares (SS_total = 81,753.850). The residual sum of squares ($SS\_residual$) was 81,590.988, accounting for 99.8% of the total variability.

For the pre-retention distance difference, results are F(2, 21) = 0.150, p = 0.862. The group effect sum of squares (SS_group) was 815.263, representing about 1.4% of the total sum of squares (SS_total = 58,059.287). The residual sum of squares

Group	Comparison	Distance Improvement	Change in Standard Deviation
Club	Pre-Post	-2.819	-1.562
Club	Pre-Retention	-6.162	6.222
Con	Pre-Post	-1.691	-6.798
Con	Pre-Retention	-19.698	-35.766
ConClub	Pre-Post	-7.694	-14.436
ConClub	Pre-Retention	-16.861	4.230

Table A.14: Mean Distance Improvement and Change in Standard Deviation by Group and Comparison Phase

($SS\_residual$) was 57,244.024, comprising 98.6% of the total variance.

Comparing the two analyses, the F-statistic for the pre-retention difference (F = 0.150) was higher than that of the pre-post difference (F = 0.021), indicating a relatively larger, though still minimal, between-group variance in the retention phase. The group sum of squares increased from 162.862 in the pre-post analysis to 815.263 in the pre-retention analysis, suggesting a slight amplification of group-based differences over time.

The total sum of squares decreased from 81,753.850 in the pre-post analysis to 58,059.287 in the pre-retention analysis, potentially reflecting a reduction in overall variability of distance differences during the retention period.

Source	Sum of Squares	df	F	p-value
Group	162.862	2	0.021	0.979
Residual	81590.988	21		

Table A.15: ANOVA results for Pre-Post Distance Difference

Source	Sum of Squares	df	F	p-value
Group	815.263	2	0.150	0.862
Residual	57244.024	21		

Table A.16: ANOVA results for Pre-Retention Distance Difference

A.4 Performance data averaged by participant test trial (Absolute Deviation)

Table A.17: Performance Data (Absolute deviation)

Group	Participant_ID	Test_Type	Release_Angle	Ball's_Distance
Con	1	Post-test	1.096600	151.214900
Con	1	Pre-test	2.281300	197.629300
Con	1	Re-test	1.188200	110.104400
Con	2	Post-test	1.333900	60.493100
Con	2	Pre-test	1.202000	113.228000
Con	2	Re-test	2.114900	114.633200
Club	3	Post-test	2.179100	147.702900
Club	3	Pre-test	3.717700	122.994800
Club	3	Re-test	6.017300	140.868900
Club	4	Post-test	2.518600	90.526400
Club	4	Pre-test	1.804900	88.113400
Club	4	Re-test	1.381600	113.416400
Con	5	Post-test	1.229400	129.403300
Con	5	Pre-test	1.138100	114.946900
Con	5	Re-test	1.366300	118.117800
Con	6	Post-test	2.528400	161.191100
Con	6	Pre-test	1.840400	112.003000
Con	6	Re-test	1.426600	157.674000
Con	7	Post-test	1.150000	118.252800
Con	7	Pre-test	1.556800	94.628500
Con	7	Re-test	2.210100	123.856500
Con	8	Post-test	4.224200	182.271200
Con	8	Pre-test	1.813200	116.508100
Con	8	Re-test	2.475600	120.984300
Con	9	Post-test	2.315000	195.334400
Con	9	Pre-test	2.252500	78.734300
Con	9	Re-test	2.770700	119.540500
Con	10	Post-test	1.019400	73.920400
Con	10	Pre-test	1.999500	128.164700
Con	10	Re-test	1.306100	97.001800
ConClub	11	Post-test	1.685600	152.293400
ConClub	11	Pre-test	1.903100	130.531900
ConClub	11	Re-test	1.685200	108.723500
ConClub	12	Post-test	2.074300	125.346600

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Table A.17 continued from previous page

Group	Participant_ID	Test_Type	Release_Angle	Ball's_Distance
ConClub	12	Pre-test	3.045100	138.021000
ConClub	12	Re-test	1.533900	111.870300
ConClub	13	Post-test	1.588700	103.944600
ConClub	13	Pre-test	2.020100	174.518100
ConClub	13	Re-test	2.141600	121.439500
ConClub	14	Post-test	2.466700	107.052500
ConClub	14	Pre-test	1.100800	144.358500
ConClub	14	Re-test	3.767000	178.214700
Club	15	Post-test	1.388400	85.327900
Club	15	Pre-test	0.830300	118.875100
Club	15	Re-test	1.326800	96.848500
Club	16	Post-test	2.137600	94.002700
Club	16	Pre-test	1.253100	104.747100
Club	16	Re-test	1.435500	96.318800
ConClub	17	Post-test	1.524200	207.512900
ConClub	17	Pre-test	1.644400	121.774700
ConClub	17	Re-test	1.987400	176.233300
Club	18	Post-test	1.558000	111.702400
Club	18	Pre-test	3.924400	93.682700
Club	18	Re-test	1.355200	110.977800
ConClub	19	Post-test	1.232700	104.578500
ConClub	19	Pre-test	2.972800	102.562900
ConClub	19	Re-test	1.706600	106.859100
Club	20	Post-test	0.862400	87.982300
Club	20	Pre-test	1.276200	118.167000
Club	20	Re-test	1.163200	86.316600
ConClub	21	Post-test	5.052300	147.875400
ConClub	21	Pre-test	1.723000	145.903300
ConClub	21	Re-test	1.474400	120.319800
Club	22	Post-test	1.022300	33.278700
Club	22	Pre-test	0.792800	56.580400
Club	22	Re-test	2.379300	52.550300
Club	23	Post-test	0.955100	63.225600
Club	23	Pre-test	1.650600	147.232400
Club	23	Re-test	0.786000	117.861600

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Table A.17 continued from previous page

Group	Participant_ID	Test_Type	Release_Angle	Ball's_Distance
ConClub	24	Post-test	2.948200	197.698200
ConClub	24	Pre-test	2.547700	222.023400
ConClub	24	Re-test	2.601000	204.329000

A.5 Data on the value of differences between test (Absolute deviation)

Table A.18: Performance data of differences between tests (Absolute deviation)

Group	Participant_ID	Comparison	Angle_Difference	Distance_Difference
Con	1	Pre-Post	-1.391567	-146.088458
Con	1	Post-Re	1.350719	-240.708772
Con	1	Pre-Re	-1.355584	-154.550534
Con	2	Pre-Post	-0.107698	-68.795091
Con	2	Post-Re	-1.345624	-104.538480
Con	2	Pre-Re	0.645030	-44.764526
Club	3	Pre-Post	0.472699	3.721131
Club	3	Post-Re	-2.963672	96.244274
Club	3	Pre-Re	2.005221	-60.876830
Club	4	Pre-Post	0.707800	46.050168
Club	4	Post-Re	0.640638	-67.102620
Club	4	Pre-Re	-0.637262	44.223240
Con	5	Pre-Post	-0.362497	-70.645967
Con	5	Post-Re	0.040968	-67.925800
Con	5	Pre-Re	-0.044266	-67.926216
Con	6	Pre-Post	0.812080	62.827627
Con	6	Post-Re	1.899099	66.415454
Con	6	Pre-Re	-0.475991	66.419423
Con	7	Pre-Post	-0.240568	-35.925329
Con	7	Post-Re	-0.870160	-23.891674
Con	7	Pre-Re	0.873946	-23.895888
Con	8	Pre-Post	0.009738	106.840046
Con	8	Post-Re	0.138908	-16.125530

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Table A.18 continued from previous page

Group	Participant_ID	Comparison	Angle_Difference	Distance_Difference
Con	8	Pre-Re	-0.141899	-16.120893
Con	9	Pre-Post	1.600775	128.822266
Con	9	Post-Re	2.024510	19.194108
Con	9	Pre-Re	2.023648	13.838329
Con	10	Pre-Post	-0.233522	9.441872
Con	10	Post-Re	1.317109	-69.419138
Con	10	Pre-Re	-0.799432	69.422277
ConClub	11	Pre-Post	1.041447	35.011256
ConClub	11	Post-Re	-1.213763	7.935337
ConClub	11	Pre-Re	1.215294	7.933313
ConClub	12	Pre-Post	-1.293272	-33.871928
ConClub	12	Post-Re	2.345109	54.853994
ConClub	12	Pre-Re	-2.343286	-54.851730
ConClub	13	Pre-Post	0.198575	-8.854193
ConClub	13	Post-Re	0.676621	-51.390553
ConClub	13	Pre-Re	-0.648026	-33.173492
ConClub	14	Pre-Post	0.722834	-34.921354
ConClub	14	Post-Re	1.365022	-24.701910
ConClub	14	Pre-Re	1.367919	-24.700981
Club	15	Pre-Post	0.459569	-17.832834
Club	15	Post-Re	-0.286641	-81.760116
Club	15	Pre-Re	0.286768	-60.817648
Club	16	Pre-Post	-0.046368	-21.713100
Club	16	Post-Re	0.796710	27.567338
Club	16	Pre-Re	-0.801358	-27.571913
ConClub	17	Pre-Post	-0.609960	7.741388
ConClub	17	Post-Re	0.475994	-68.043485
ConClub	17	Pre-Re	-0.471913	8.106052
Club	18	Pre-Post	-2.444624	-0.753226
Club	18	Post-Re	-1.660776	-28.223337
Club	18	Pre-Re	-1.663763	-11.577700
ConClub	19	Pre-Post	0.150738	-44.309724
ConClub	19	Post-Re	-0.649853	28.885587
ConClub	19	Pre-Re	-0.189448	-28.884451
Club	20	Pre-Post	-0.097594	1.484366

Continued on next page

Table A.18 continued from previous page

Group	Participant_ID	Comparison	Angle_Difference	Distance_Difference
Club	20	Post-Re	-0.072327	-67.483382
Club	20	Pre-Re	-0.071898	66.745347
ConClub	21	Pre-Post	3.097825	73.674228
ConClub	21	Post-Re	-1.305872	-15.804374
ConClub	21	Pre-Re	-0.398128	-2.615850
Club	22	Pre-Post	0.491829	-16.445828
Club	22	Post-Re	1.981875	33.528953
Club	22	Pre-Re	1.222882	-29.074607
Club	23	Pre-Post	-0.631784	-17.061520
Club	23	Post-Re	0.872033	29.653739
Club	23	Pre-Re	-0.872520	29.658425
ConClub	24	Pre-Post	1.118147	-56.017763
ConClub	24	Post-Re	-0.766106	-6.694897
ConClub	24	Pre-Re	0.770945	-6.691398

Appendix B

Kinematic data

B.1 Kinematic Analysis: Sternum Rotation

Group	Test Phase	Mean	Std. Dev.	Minimum	Maximum
Con	Pre-test	1.71	6.48	-19.01	21.04
Con	Post-test	1.25	7.28	-18.80	20.63
Con	Re-test	0.31	5.80	-21.98	18.43
ConClub	Pre-test	2.62	8.13	-17.81	27.60
ConClub	Post-test	1.66	5.13	-10.76	22.18
ConClub	Re-test	1.69	5.47	-13.30	17.46
Club	Pre-test	1.66	5.92	-11.36	17.38
Club	Post-test	1.19	4.25	-7.18	11.76
Club	Re-test	0.80	4.61	-11.16	12.66

Table B.1: Euler Angle Statistics Across Groups and Test Phases

The **Club** group (as shown in Figure 4.4) demonstrated a consistent decrease in oscillation amplitude from pre-test (M = 1.66, SD = 5.92) to post-test (M = 1.19, SD = 4.25), with retention of intervention effects indicated by the re-test (M = 0.80, SD = 4.61). Rotation peak timing was stable across all tests.

The **ConClub** group (as shown in Figure 4.6) displayed more complex changes. Post-test amplitude (M = 1.66, SD = 5.13) decreased relative to pre-test (M = 2.62, SD = 8.13) with earlier phase peaks. Re-test amplitude (M = 1.69, SD = 5.47) showed partial recovery but remained lower than pre-test levels. Phase patterns in the re-test nearly reverted to pre-test conditions.

For the **Con** group (Figure 4.5), the post-test amplitude (M = 1.25, SD = 7.28) showed a increase from the pre-test (M = 1.71, SD = 6.48) but with a slightly higher SD, suggesting increased variability. In the re-test (M = 0.31, SD = 5.80), the ampli-

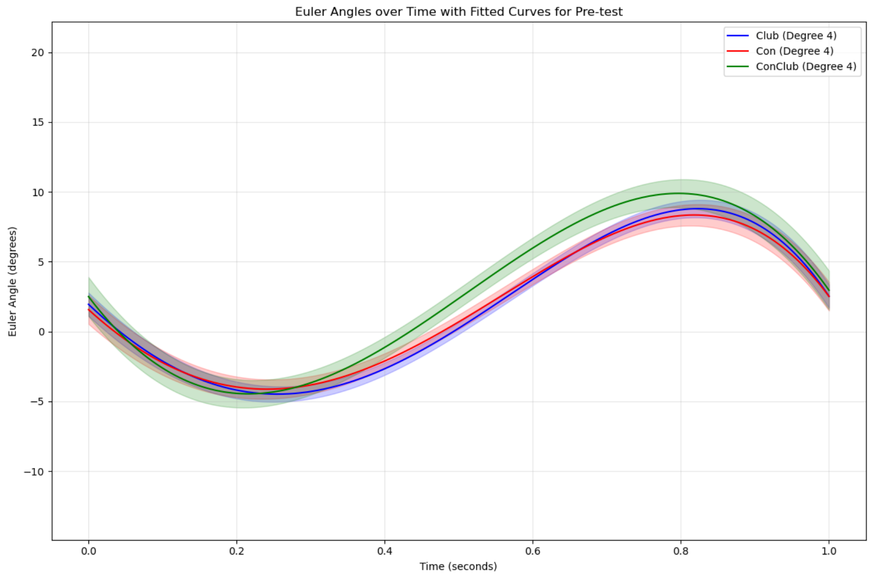

Figure B.1: Comparison of Euler Angles Over Time for Three Groups During Pre-test

tude returned to near pre-test levels, with a reduced SD.

In summary, interventions differentially affected sternal rotational kinematics: ConClub induced transient changes in amplitude and swing moments; Club demonstrated sustained amplitude changes with stable swing moments; Con exhibited minimal alterations in both parameters.

B.2 Euler angle plot with different groups

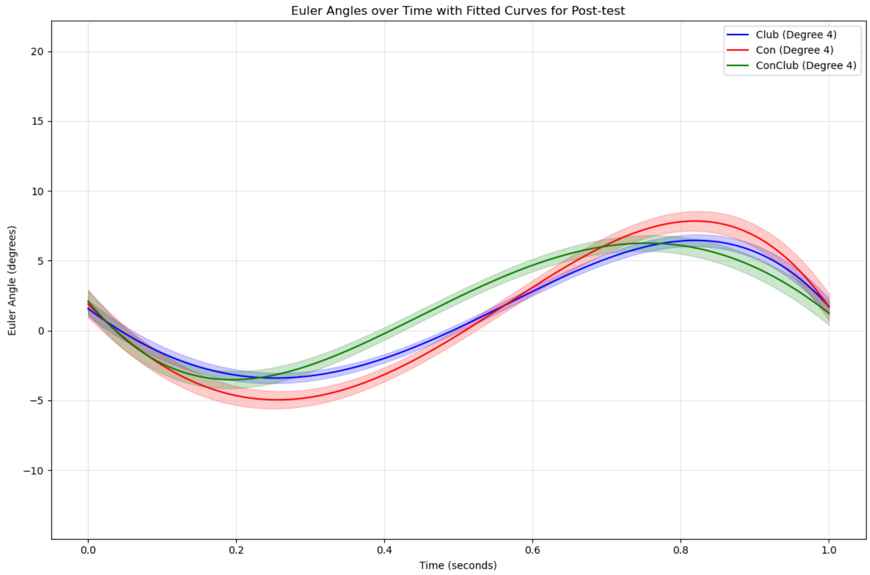

Figure B.2: Comparison of Euler Angles Over Time for Three Groups During Post-test

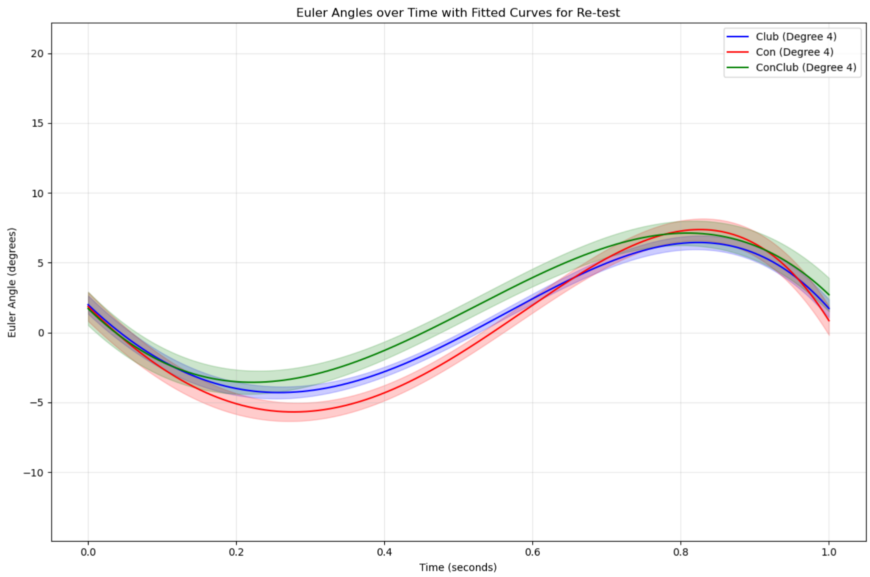

Figure B.3: Comparison of Euler Angles Over Time for Three Groups During Re-test

Appendix C

Results of normality and homogeneity tests

C.0.1 Radial Error Differences Between Test Phases

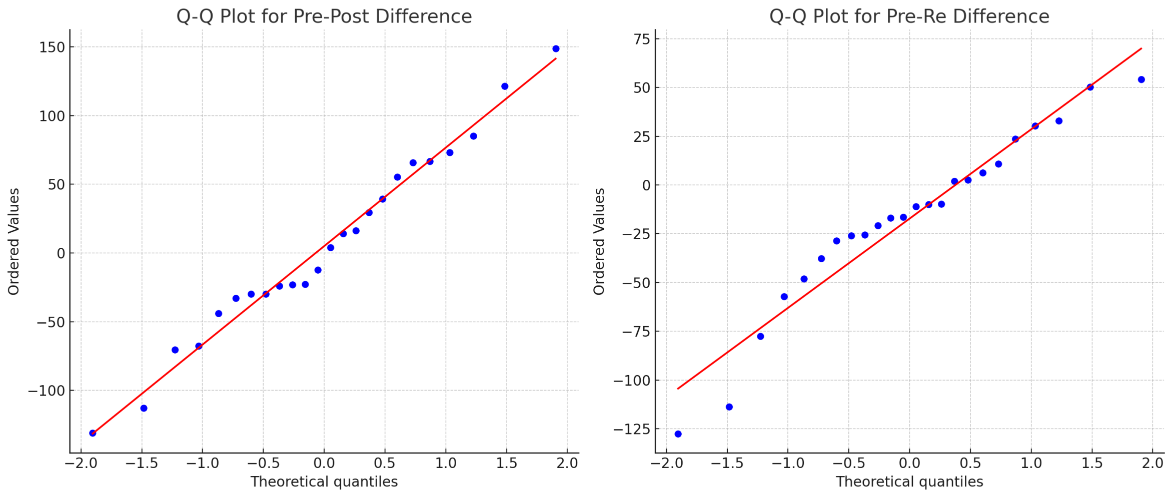

Figure C.1: QQ plot for radial error difference between different test

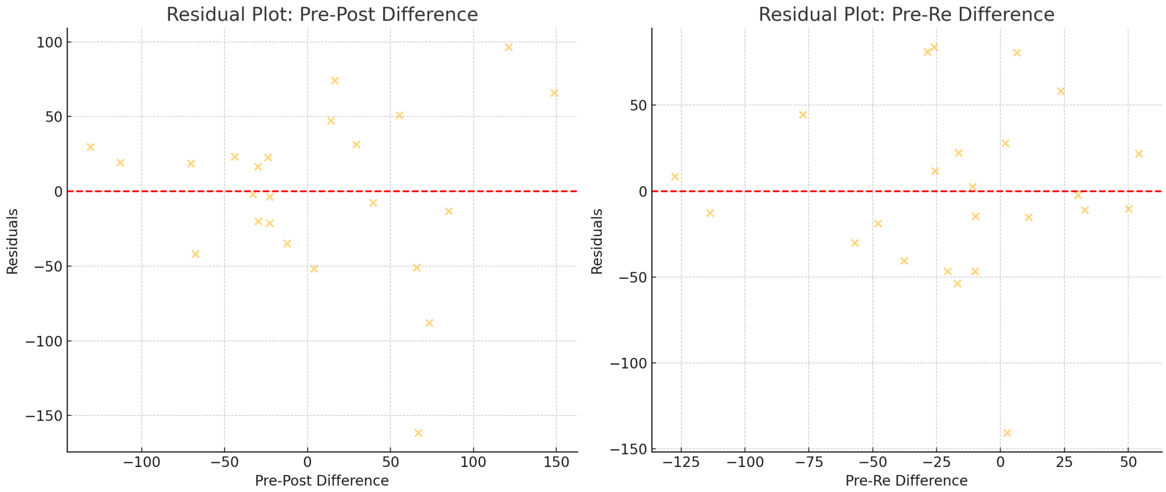

Figure C.2: Residual plot for radial error difference between different test

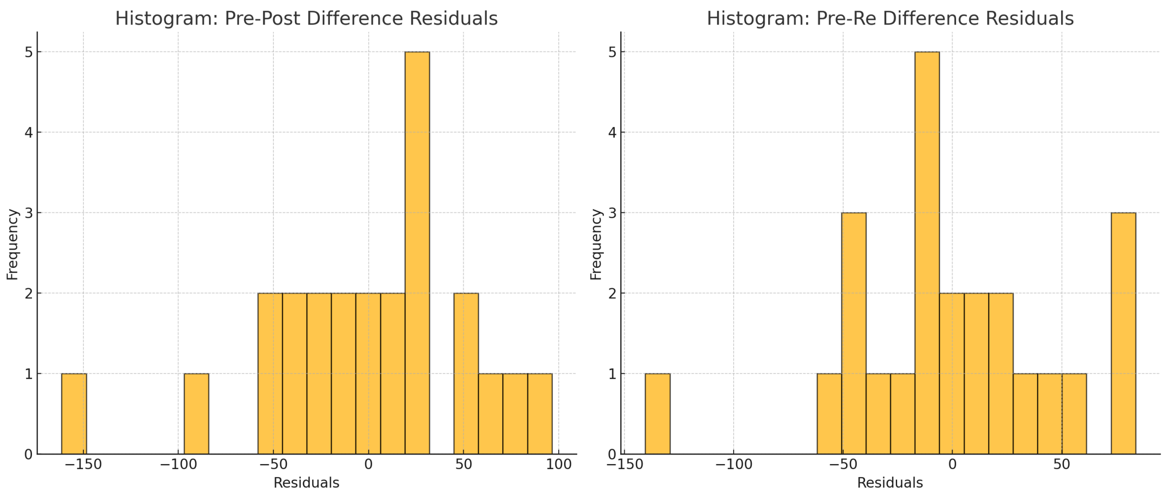

Figure C.3: The histograms for the residuals of the Pre-Post Difference and Pre-Re Difference

C.0.2 Initial Release Angle Differences Between Test Phases

Pre-Post Differences

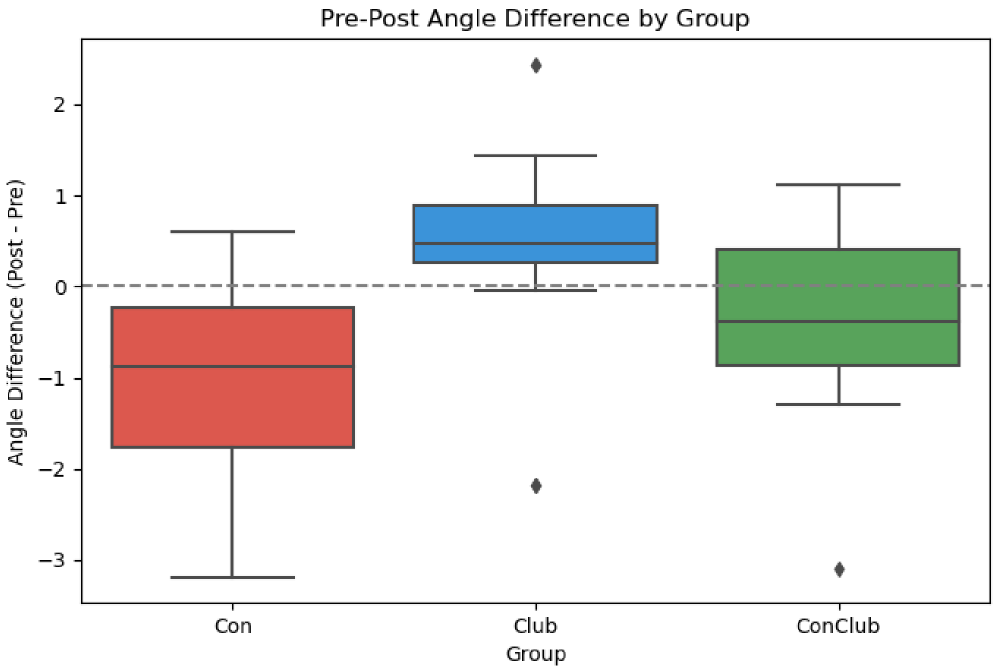

Figure C.4: Box plot for angle difference between pre- and post test

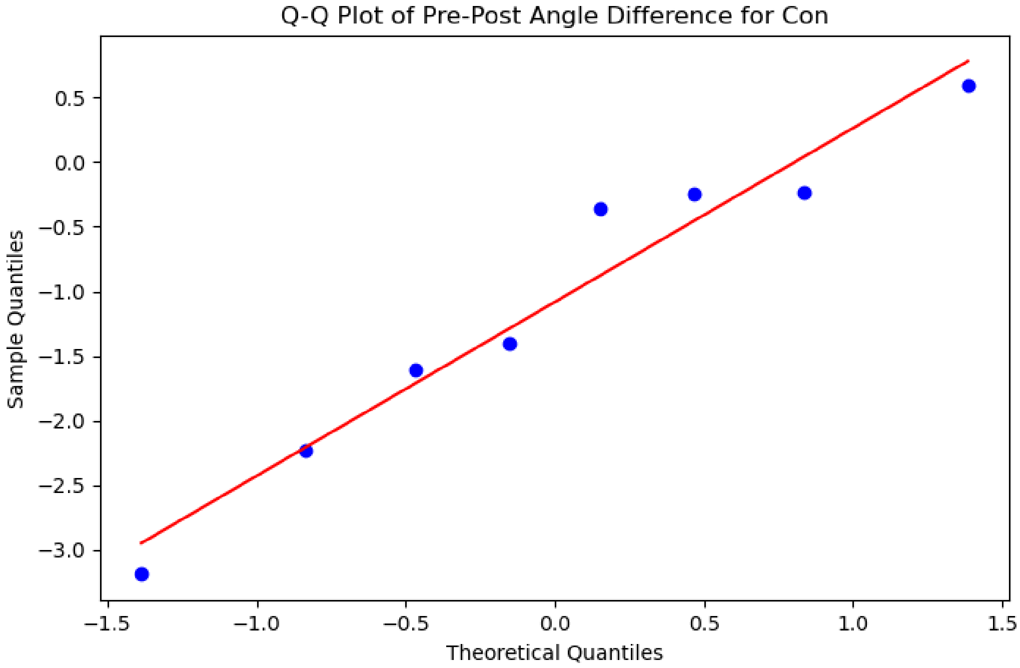

Figure C.5: QQ plot for angle difference between pre- and post test (Con group)

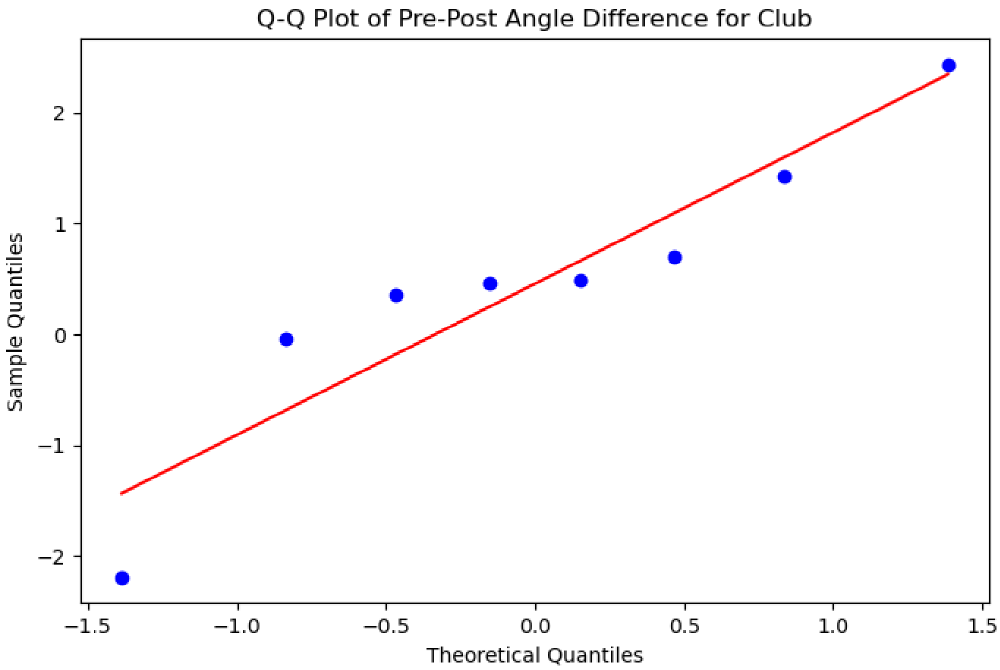

Figure C.6: QQ plot for angle difference between pre- and post test (Club group)

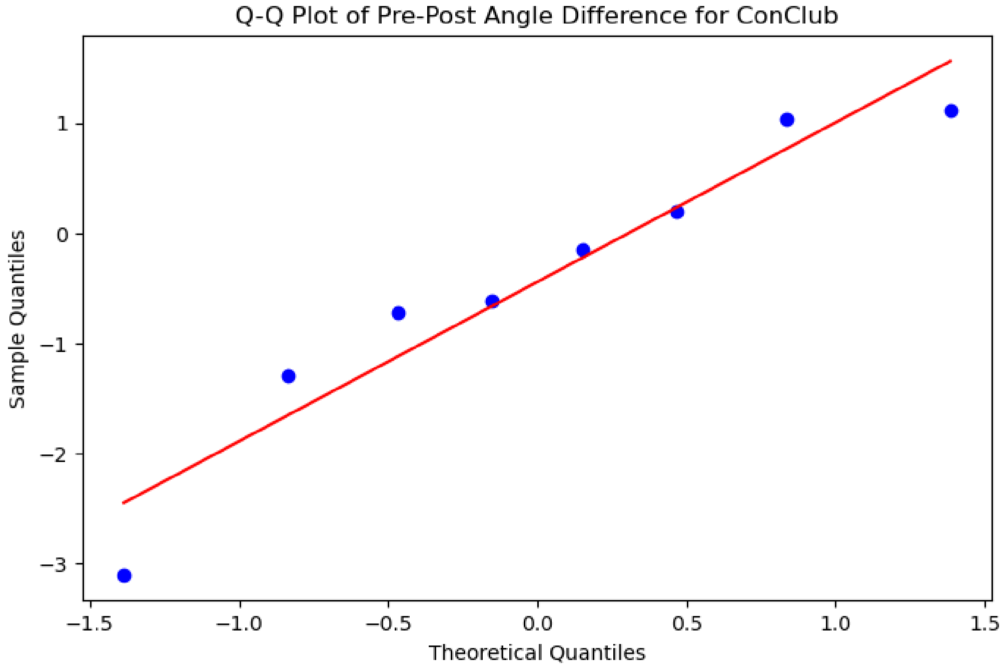

Figure C.7: QQ plot for angle difference between pre- and post test (ConClub group)

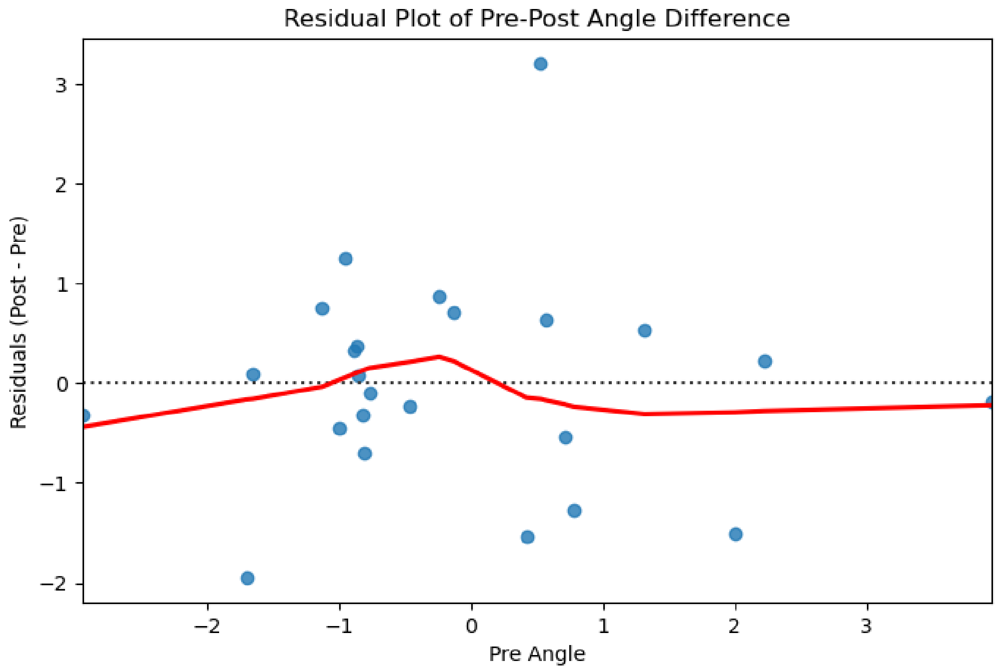

Figure C.8: Residual plot for angle difference between pre- and post test

Pre-Retention Differences

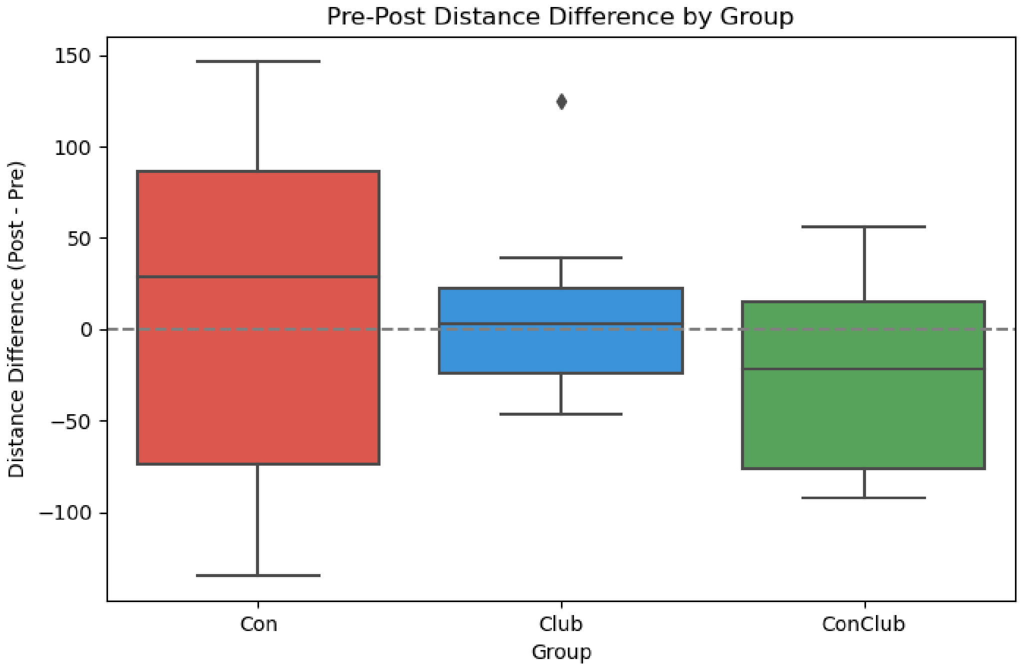

Figure C.9: Box plot for angle difference between pre- and retention test

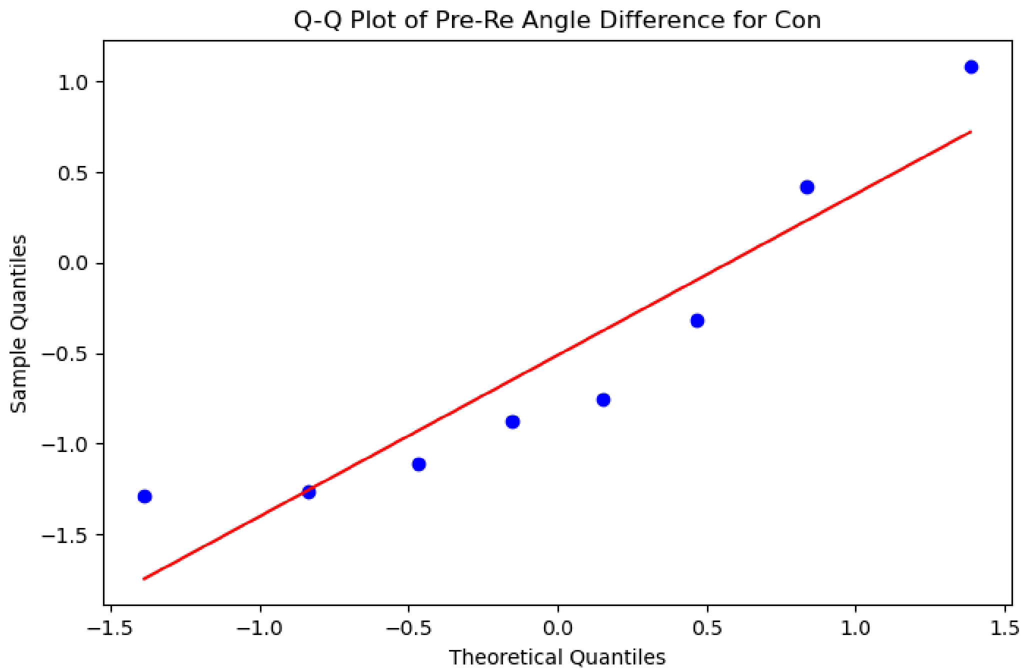

Figure C.10: QQ plot for angle difference between pre- and retention test (Con group)

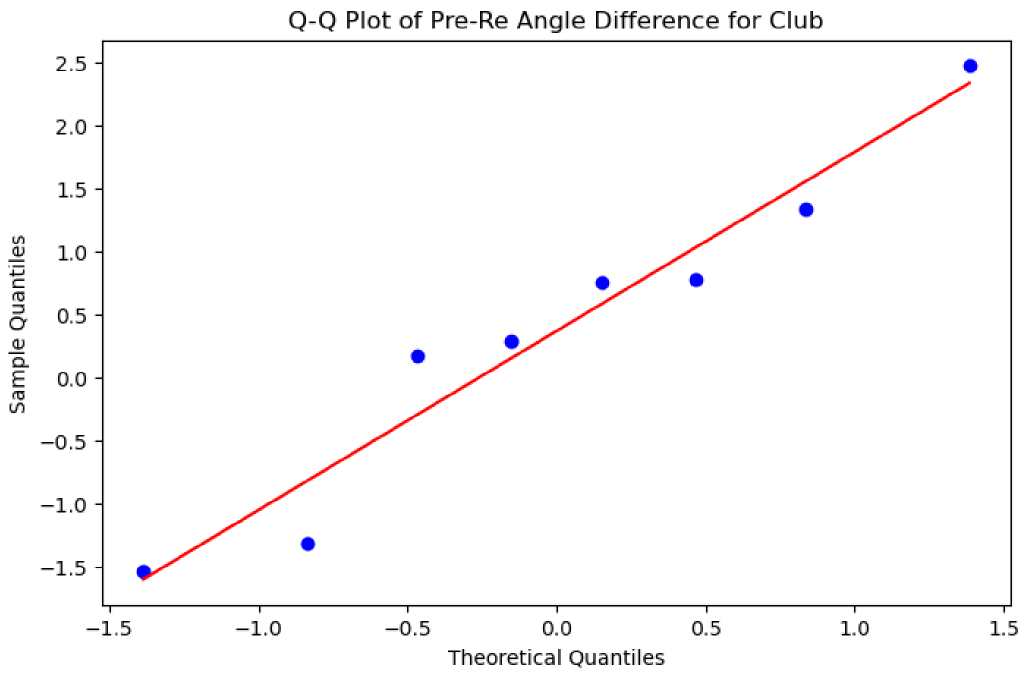

Figure C.11: QQ plot for angle difference between pre- and retention test (Club group)

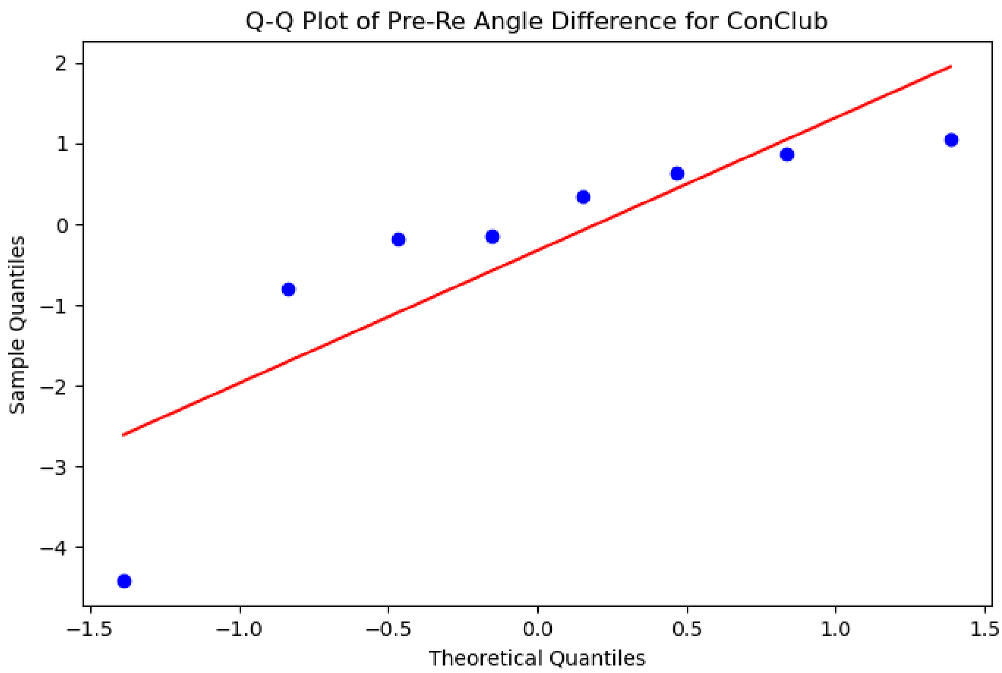

Figure C.12: QQ plot for angle difference between pre- and retention test (ConClub group)

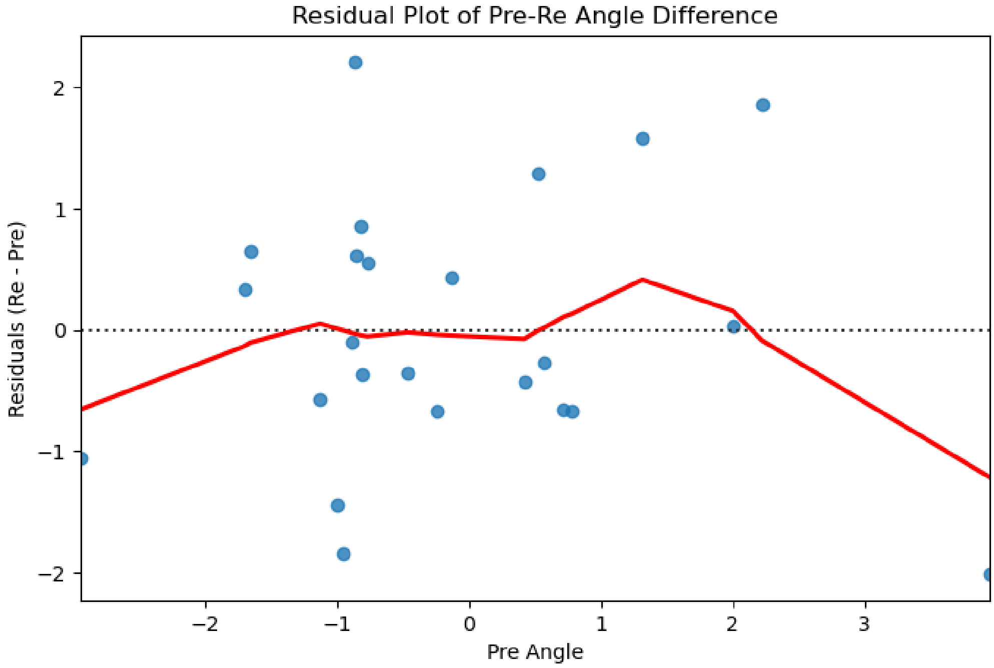

Figure C.13: Residual plot for angle difference between pre- and retention test

C.0.3 Ball's Travel Distance Differences Between Test Phases

Pre-Post Differences

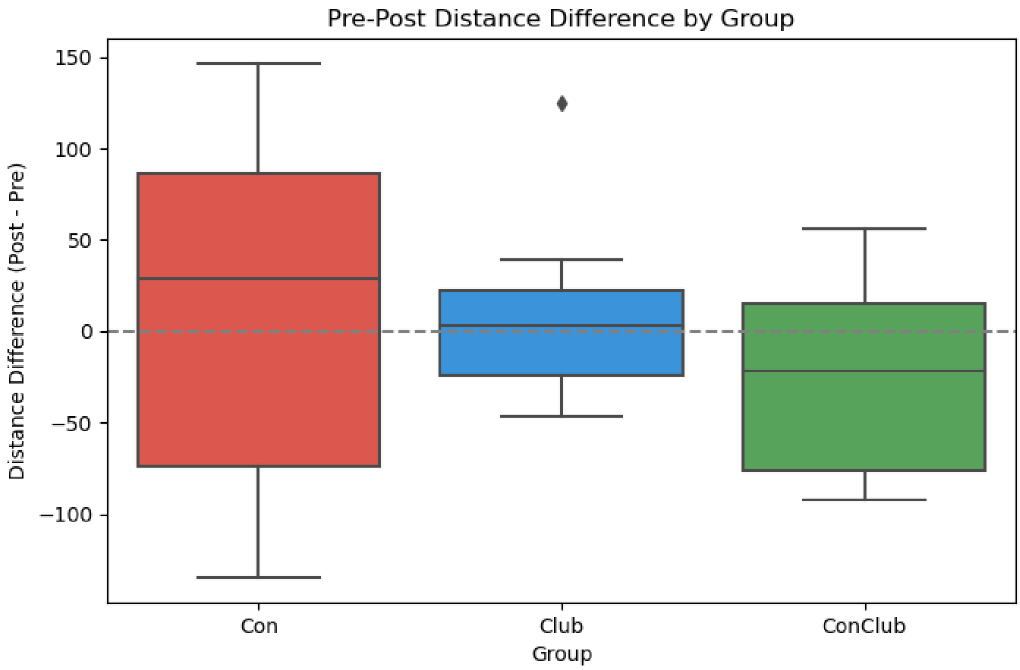

Figure C.14: Box plot for distance difference between pre- and post test

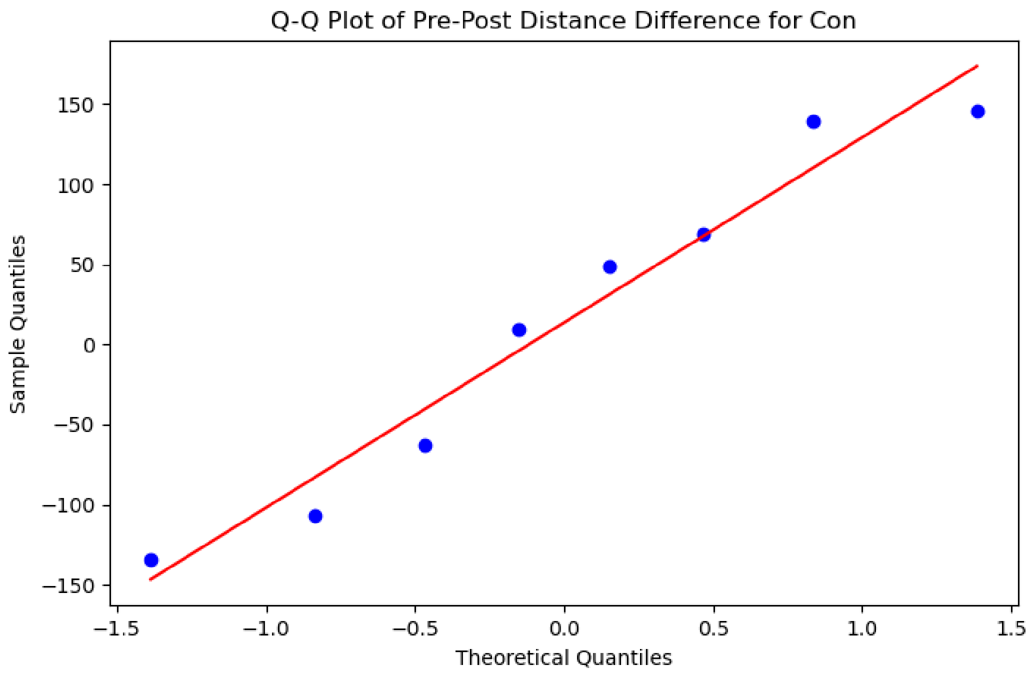

Figure C.15: QQ plot for distance difference between pre- and post test (Con group)

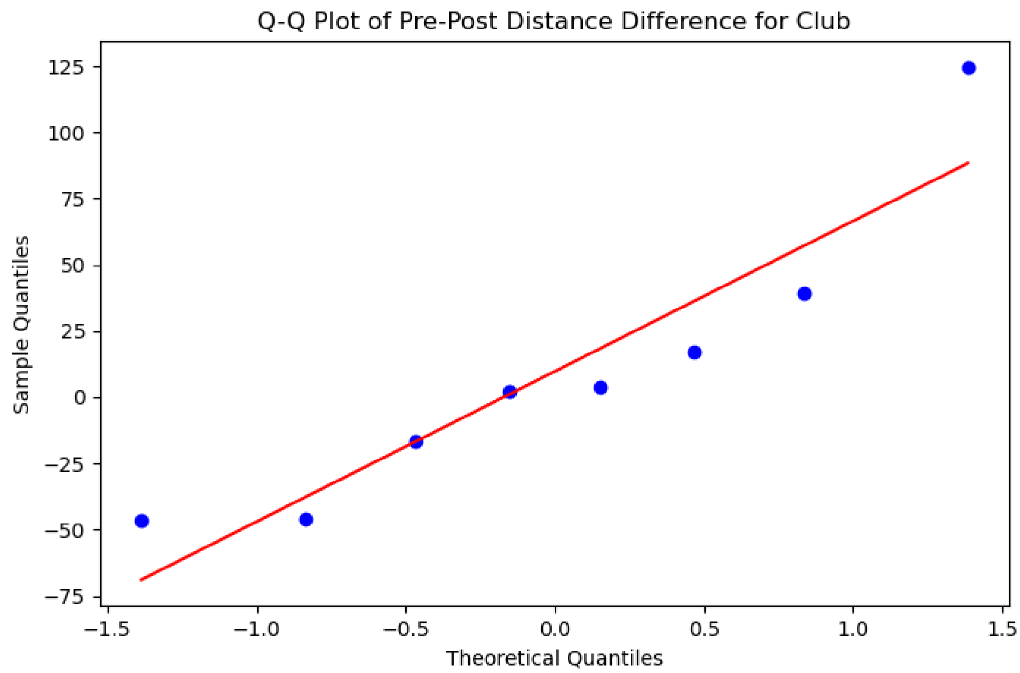

Figure C.16: QQ plot for distance difference between pre- and post test (Club group)

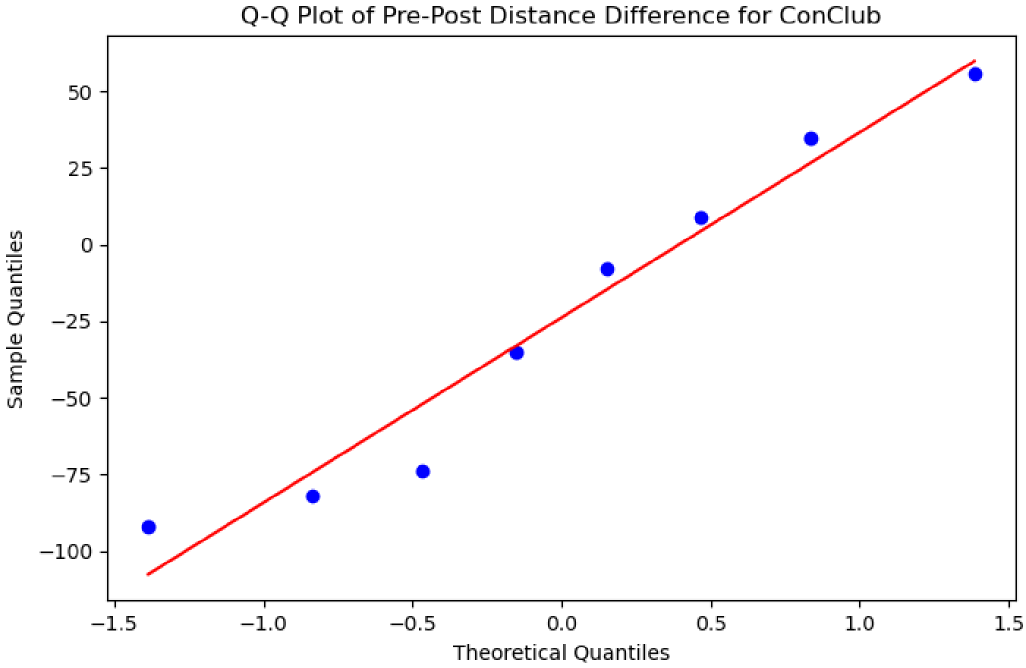

Figure C.17: QQ plot for distance difference between pre- and post test (ConClub group)

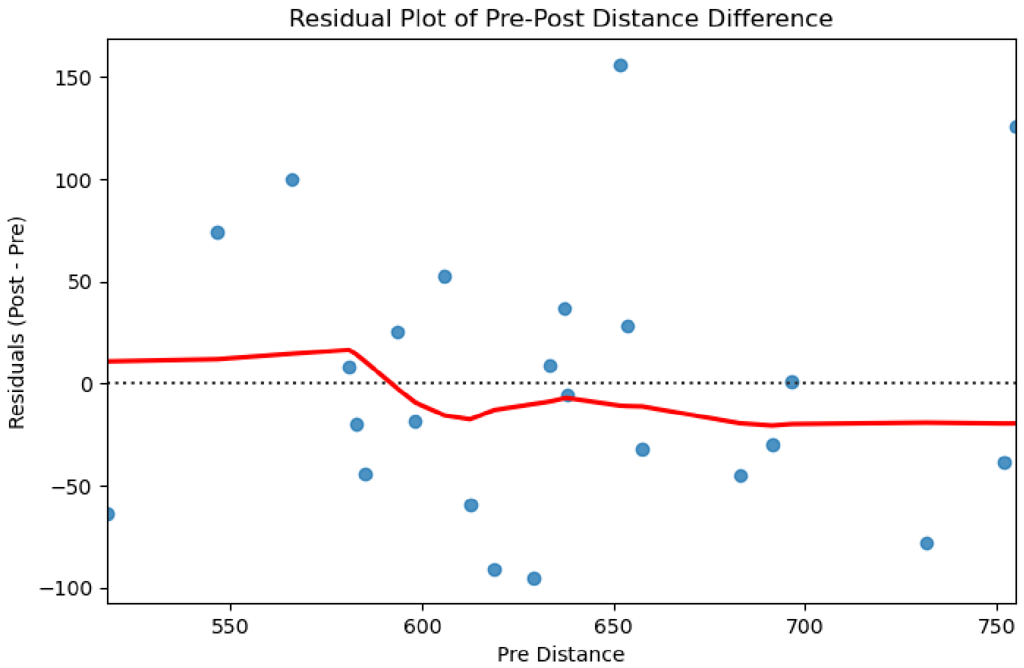

Figure C.18: Residual plot for distance difference between pre- and post test

Pre-Retention Differences

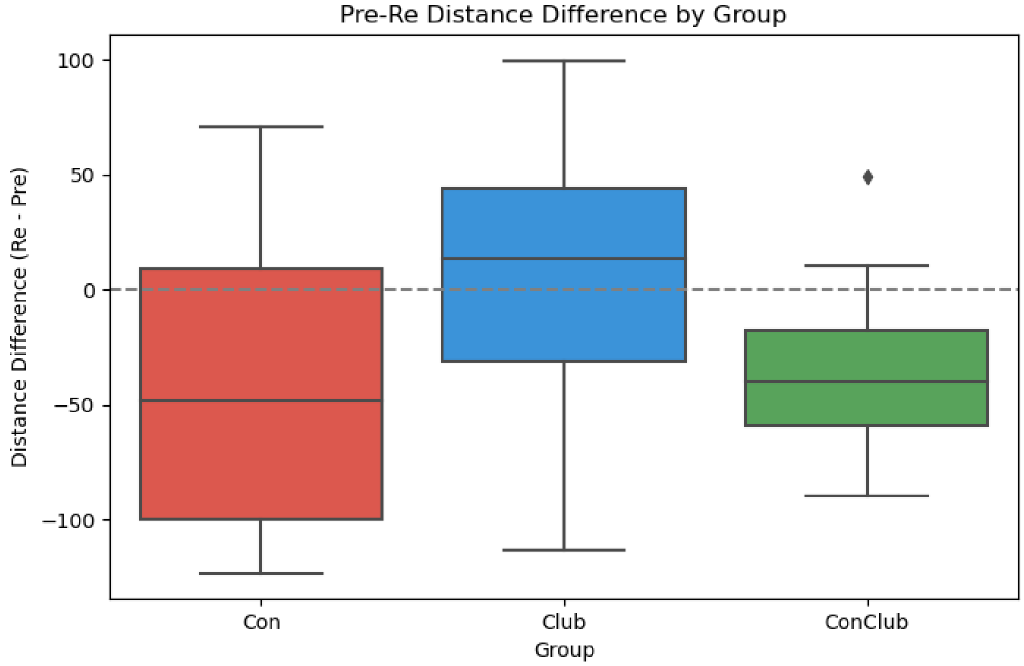

Figure C.19: Box plot for distance difference between pre- and retention test

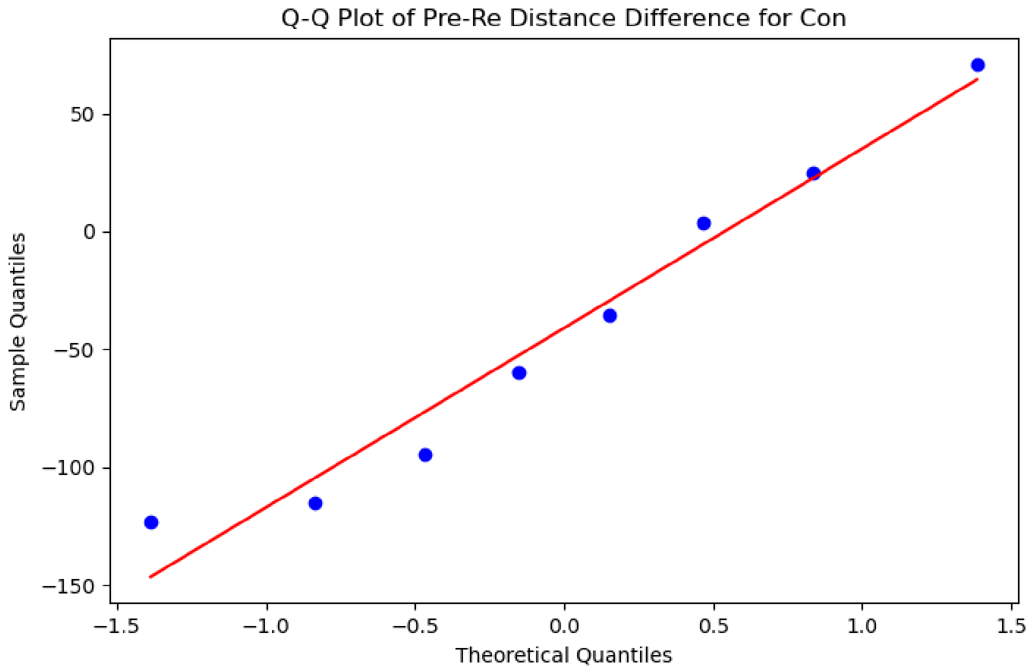

Figure C.20: QQ plot for distance difference between pre- and retention test (Con group)

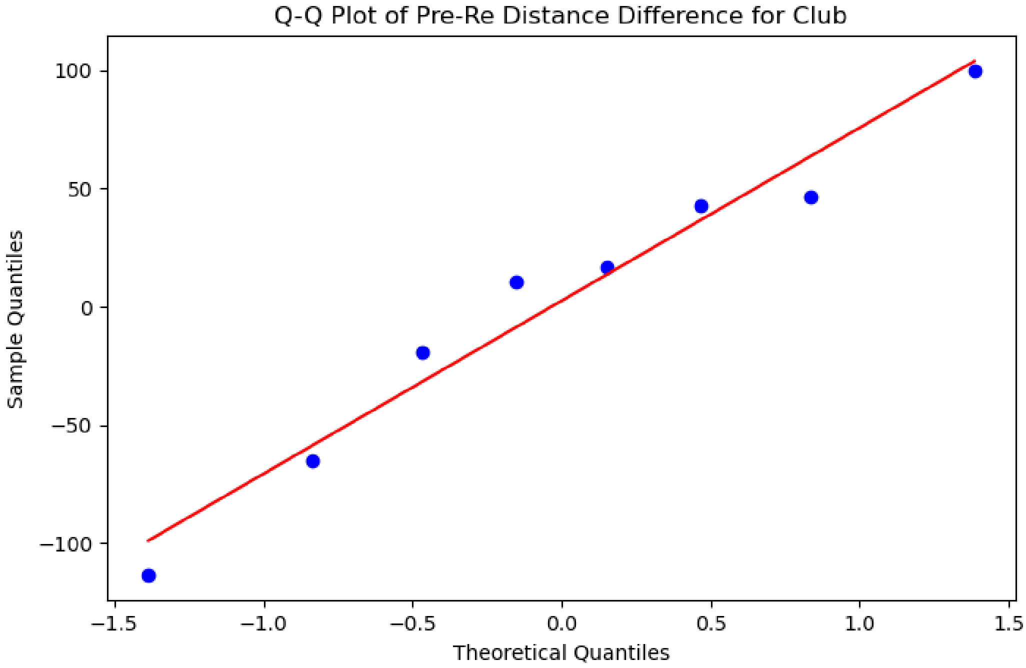

Figure C.21: QQ plot for distance difference between pre- and retention test (Club group)

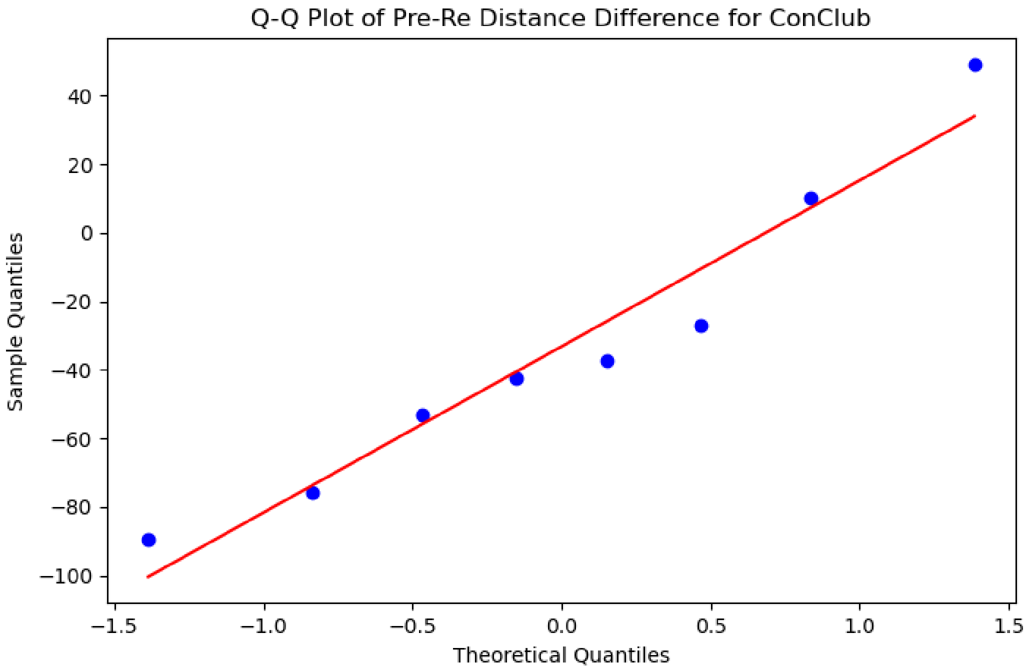

Figure C.22: QQ plot for distance difference between pre- and retention test (ConClub group)

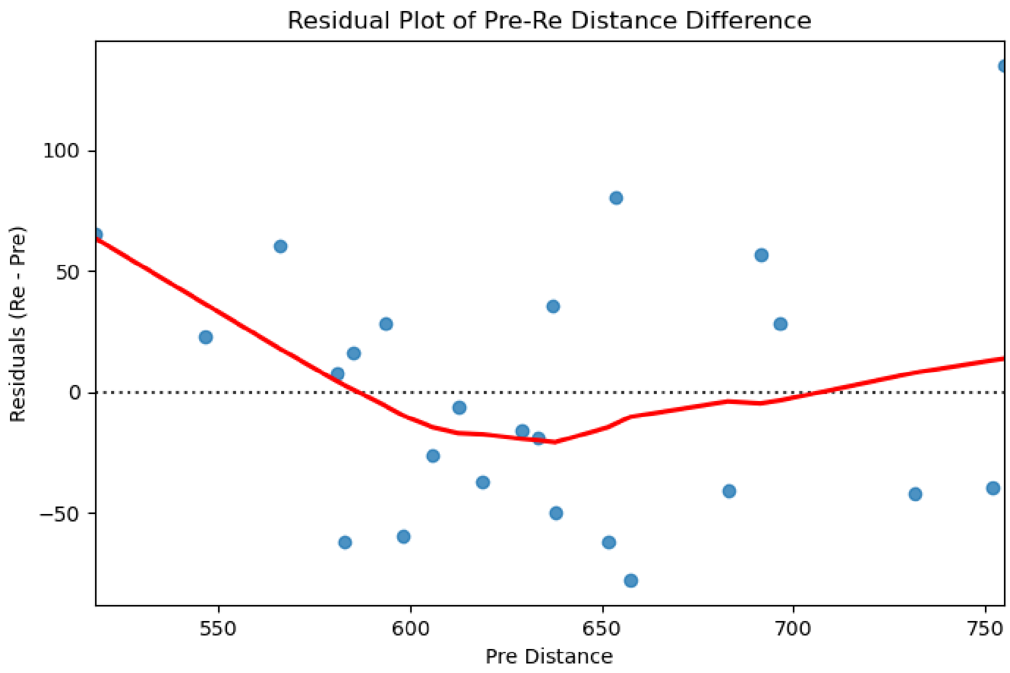

Figure C.23: Residual plot for distance difference between pre- and retention test

Appendix D

Interview data

D.1 Interview transcripts

Interview 1 (Con)

```
Questioner: First question, in the VR environment, do you feel
    uncomfortable?
Answerer: No, not really.
Answerer: Oh, a little bit, but I'm thinking that's just how VR is.
    Okay.
Questioner: How would you describe the feeling of playing golf in the
    real world?
Answerer: In the real world, compared to VR? Or just purely... purely
    ...
Questioner: Purely, purely the feeling.
Answerer: It feels very...
Answerer: Fresh.
Questioner: Okay, what's the difference between the feedback you feel
    in VR and in the real world?
Answerer: In VR, the circles light up when you hit them.
Answerer: Yeah, it tells me right away that I can add eight points. In
     terms of feel, the controller is lighter compared to a real golf
    club.
Questioner: Different, okay. Did using the controller in VR help you
    ...
Questioner: ...adapt to the real world faster?
Answerer: I think it did in the end. But while I was doing it, it didn
    't feel like it. Yeah.
Answerer: Yeah, it's just... it's a bit too light.
Questioner: Ah, so you're saying... If you use a real club during
    training...
Questioner: ...what impact would that have on your performance? In
    training, you said...
Answerer: Uh, what impact would it have? It would...
```

```
Questioner: Would it be better? Do you think your score...
Answerer: Would be better.
Questioner: Let's move on to the next one.
Questioner: We'll leave that unanswered.
Answerer: That's a tough one. It seems like it would be better.
Questioner: Overall, do you think VR is helpful for learning golf?
Answerer: Yes, it is.
```

Interview 2 (Con)

```
Questioner: How would you describe the feeling of playing golf in the
    real world?
Answerer: How do I describe it? I've never played...
Questioner: Anything, Just tell me your impression.
Answerer: I don't know how to describe it. It's just...
Answerer: It seems to require less physical activity than other sports
    , and it focuses more on hand and waist control... waist strength
    control.
Questioner: Overall, do you think this training has helped you learn
    golf?
Answerer: Yes, I think so. After all, I've never played before.
Answerer: Okay.
```

Interview 3 (Con)

```
Questioner: First question, do you feel any discomfort in the VR
    environment? Oh, okay.
Answerer: A little bit of discomfort, maybe because...
Answerer: It's a combination of factors. The resolution, the physics
    engine, and those effects definitely have...
Questioner: Some differences, but it's okay. How would you describe
    the feeling of playing golf in the real world?
Questioner: Uh...
Answerer: Which aspects? In terms of...
Answerer: Are we comparing, or should I just talk about the real world
    ?
Questioner: Time-wise, let's compare.
Answerer: I think playing golf in the real world is...
Answerer: ...very satisfying because you're actually hitting the ball,
     and it feels great. Also...
Answerer: You might need to consider more factors. Like in VR, it
    might say there's wind, but I can't actually feel it, so I can
    only hit blindly. But in the real world, I can really feel the
    wind blowing.
```

Questioner: So what are the differences between the feedback you feel and the real-world experience? Is it the feedback from your hand in VR?
Answerer: Oh, I feel like it's not easy to judge distance in VR. I can 't really tell how far away things are, so I can only try it out first. And the haptic feedback is definitely... Because I'm just holding a controller, and the controller has almost no weight, so ...
Questioner: ...you don't feel a particularly strong weight or impact.
Answerer: Okay, right.
Questioner: Do you think your performance would improve if you used a real club to practice?
Answerer: I think it definitely would. Because, well, feeling the weight of the controller, I think, is very helpful in allowing me to control the swing.
Questioner: Good. Overall, do you think VR is helpful for learning golf?
Answerer: I think it is, depending on what aspects you're looking at.
Answerer: It can help me practice my aim and direction, and it allows me to get familiar with the overall environment and get into the swing of things faster. And a big advantage of VR is that you can hit unlimited balls without having to pick them up, so I think it greatly reduces the learning curve.
Questioner: What are its drawbacks?
Answerer: The only drawback is that it's not real enough.
Questioner: It's not real enough. So the problem with VR is the feel, right?
Answerer: Right, it's just not real enough. I don't see any other drawbacks.
Questioner: Okay.

Interview 4 (Con)

Questioner: First question, did you feel any discomfort in the VR environment?
Answerer: Yeah, a little bit. Okay. A little bit. Okay. I think yeah, it's maybe it's because I, I think like it's my second or third time. So yeah, it's... And yeah. And I think the movement, yeah, it's not as natural, I think. So, yeah. Then how do you describe the feelings of playing golf on the real field?
Answerer: I think it's...
Answerer: Better. Better. Okay, than VR.
Answerer: Because it's, yeah, it's, it's real. Like you can feel the weight of... mistake. Okay, yeah.

```
Questioner: How does the feedback you perceived in VR compared to what
    you experienced in reality? All kinds of feedback. Haptic
   feedback, visual feedback.
Questioner: What do you mean? I mean how do you feel about your hands
   when playing VR and the real world?
Answerer: I think, yeah, I think the...the...the feedback, the...the
   main feedback I think is the weight of the...of the controller and
    the...
Answerer: It's different, okay. And then when you hit the ball, there'
   s some kind of, you know, like you feel the hit, but in VR you don
   't feel the hit.
Questioner: Yeah, true, true. Do...
Questioner: Do you think training with the controller in VR help you
   adapt to the real world faster?
Answerer: Maybe I would say no.
Questioner: Okay, how do you think it would affect your performance if
    you use the real club during training? Your performance improved?
Answerer: I think if you use a real stick, maybe it can improve.
Questioner: Okay, overall, do you think VR helped you learn golf?
Answerer: Yeah, not... yeah, a little bit maybe, but not like a big...
    Okay, yeah, but a little bit, sure, but not... yeah, yeah.
```

Interview 5 (Con)

```
Questioner: Did you feel any discomfort in the VR environment?
Answerer: Overall, I didn't feel uncomfortable. Everything is okay.
Questioner: Good. How would you describe the feeling of playing Golf
   in the real world?
Answerer: The feeling of the club is the most obvious difference,
   because the club head has weight.
Answerer: So when putting, you can clearly feel the force of the club.
    But in VR...
Answerer: ...it's actually quite different. The VR club is very light,
    the controller is very light, and you don't have that sense of
   weight or how the weight hangs. The way you grip the club is
   completely different. And in VR, your field of view is limited.
Answerer: ...in real life, my field of view is wider, and I can judge
   the distance between the ball and the target much faster and
   easier. But in VR, I need to turn my head more to determine the
   position and direction.
Questioner: You know how...
Answerer: And another difference is the VR... the...
Answerer: The VR headset is heavy, and when it's on your head, it's
   relatively uncomfortable to look down.
```

```
Questioner: Do you think training with the controller in VR will help
   you adapt to real-world skills faster?
Answerer: I don't know why, but I...I...I think it will help, but it
   depends on what kind of training you're doing. Because I think it'
   s good for aiming and angle training, but if you want to do
   training related to physical weight, distance... I mean, you want
   it to hit the target at a specific angle and not too far off. That
    kind of training is okay because you can control the direction of
    the club, the direction of your swing. But for distance training
   ...
Answerer: ...like how far and close this ball will go, I don't think
   it's as good as I imagined. And when I play in VR, I feel like my
   hand is shaking very obviously, it's hard to control the
   steadiness. But in real life, I feel like my hands are more stable
   , maybe...
Answerer: ...because the club has weight, I'm not sure. What do you
   think is the impact of using a real club during this training on
   your final performance?
Questioner: Okay.
Answerer: It will be better. It would definitely be better to use a
   real club during VR training.
Questioner: Okay. Overall, do you think VR is helpful for learning
   golf?
Answerer: Oh, I think it is, especially when you have limited space
   and you don't have to pick up the balls.
Answerer: Yes, yes. And one thing that's very different is that in VR,
    when the club hits the ground, it feels very strange. It doesn't
   feel like a real club hitting the ground.
Questioner: Okay, thank you.
```

Interview 6 (Con)

```
Questioner: Did you feel any discomfort in the VR environment?
Answerer: Uh, no.
Questioner: How would you describe the feeling of playing golf in the
   real world?
Answerer: In the real world, it feels like, uh...
Answerer: ...the ball... the feeling of hitting the ball is longer. I
   mean, the club and the ball are in contact for a longer time, and
   then the force...
Questioner: What's the difference between the feedback you feel in VR
   and in reality?
Answerer: Uh, in VR, it's relatively light, whether it's the impact or
    the force when you swing. The feedback in the real world is much
   stronger.
```

Questioner: Do you think training with this club controller in VR has helped you adapt to the real world faster?

Answerer: Uh, yes. It’s obvious that ...my backswing is more stable now.

Questioner: If you were to use a real club in real training, do you think your performance would improve or decline?

Answerer: I think it would improve.

Questioner: Overall, do you think VR is helpful for learning golf?

Answerer: Yes, it is helpful.

Questioner: That’s all.

Interview 7 (ConClub)

Questioner: Did you feel any discomfort in the environment?

Answerer: Not really, it’s okay, I don’t feel dizzy.

Questioner: How would you describe the feeling of playing in the real world?

Answerer: It feels like golf. I think the physical feedback from the ball is stronger compared to VR. Because of the sound of the impact and being able to see the direction of the club in my hand, it’s easier to control. But when switching from VR to the real world, the force required is different, so...

Questioner: It takes adjustment. Do you think training with the controller in VR helped you adapt to the real world faster?

Answerer: I think if I had grasped the knack and the positioning, it would have been helpful. But the VR environment just now had three types of terrain, some with slopes, which is different from the front, back, and sides of where I actually hit the ball. So there’s no way to tell if it has a significant effect, like quickly grasping how to do it, if you were training...

Questioner: If you were training in a real environment using real clubs, do you think you would perform better or worse?

Answerer: I think it would be more tiring because I’m easily affected by the environment, like hot weather, especially on the golf course. My performance would weaken a bit. VR might be...

Questioner: More convenient. Overall, do you think VR...VR...

Answerer: Helpful for learning golf? Yes.

Questioner: Is it fun?

Answerer: Hahahaha, yes, and it has glowing feedback.

Interview 8 (ConClub)

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Questioner: Did you feel any discomfort in VR?
Answerer: No, I didn't.
Questioner: How would you describe the feeling of playing golf in the
   real world?
Answerer: Oh, in the real world, the ball's weight feels a bit
   different compared to VR.
Questioner: Is there a difference between the feedback you feel in VR
   and in the real world?
Answerer: There is still some difference. In the real world, you have
   to consider various factors, not just the ball but also the
   direction and everything. But in VR, you just need to swing and
   control the strength, which is okay.
Questioner: Do you think training with the controller in VR has helped
    you adapt to the real world faster?
Answerer: Yes, it has, it has.
Questioner: If you were to use a real club during training, do you
   think your performance would improve or decline?
Answerer: It should improve, I think it should improve.
Questioner: Overall, do you think VR is helpful for learning golf?
Answerer: I think it's quite helpful, especially for beginners. Do you
    have any other opinions?
Questioner: Uh...
Answerer: No.
Answerer: I don't think so, okay?
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Interview 9 (ConClub)

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Questioner: Did you feel uncomfortable in the VR environment?
Answerer: No.
Questioner: How would you describe the feeling of playing golf in the
   real world?
Answerer: Uh, it feels much better than VR.
Questioner: Okay. How does the feedback you feel in VR compare to the
   feedback you experience in reality?
Answerer: It's very different. The accuracy, and also the...
Questioner: Mainly the accuracy.
Answerer: There's a lot of feedback...
Answerer: You feel...
Questioner: The feedback you feel, like the vibration feedback and all
    that.
Answerer: Uh, it's very average. I don't feel like I'm hitting a real
   ball. I feel like I'm just practicing my swing.
Questioner: Okay. Do you think training with the controller and club
   together in VR has helped you adapt to the real world faster?
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Answerer: It helped, but not that much. Because the swing, because the
    swing is very... very... very inaccurate, so sometimes it feels
    like I'm just gliding over the ball instead of hitting it.
Questioner: If you were to use a real club during training, do you
    think your performance would be any different? If you train with a
     real club in the real world, would your performance be better or
    worse than now? If we use the physical world as a substitute for
    VR training. Yeah, yeah, yeah. So it would be better, it would be
    better, right? Overall, do you think this VR is helpful for your
    golf learning?
Answerer: Yes, it is helpful. I think it can be used to practice a lot
     of basic skills. It's very helpful for your timing and accuracy.
    Okay, good.
```

Interview 10 (ConClub)

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Questioner: You feel any discomfort in the VR environment?
Answerer: At some point I don't know why it start to distorting.
Answerer: And that's when I feel a little bit hard to adjust with my
    environment.
Questioner: Okay. And then how would you describe the feeling of
    playing golf in the real world?
Answerer: The feeling... good question.
Answerer: Probably enjoyment and pressure.
Answerer: So excitement.
Questioner: Okay. And how does the feedback you perceive in VR
    compared to what you're experiencing in reality? Feedback from
    everything, controllers or the visual stuff?
Answerer: Okay.
Answerer: From the... I think the feedback sound a little bit loud,
    you know, on the... I don't know... so we... I use it or not, but
    I heard a lot of windy sound and I cannot like...
Answerer: When I do the...
Answerer: When... when I hit it, it's just like I don't really hit it,
     you know?
Answerer: Okay. Like... like for example like I don't feel the... the
    stick... what is called the stick?
Questioner: The stick.
Answerer: And the club, yeah. It's not really touching the balls, okay
    ? It's just like, okay, nowhere.
Questioner: And do you think training with a controller in VR help you
     adapt to the real world faster?
Answerer: Oh, well...
Answerer: I don't know.
Questioner: Okay.
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Answerer: I'm sorry, I don't know.
Questioner: How do you think it would affect your performance if you
   use the real club during training?
Answerer: Uh, because the real club is... happy...
Answerer: It was... I have sense of...
Questioner: Wait, yeah.
Answerer: Yeah, and the weight make me have a feeling how to control
   my...
Answerer: My movement and my feeling to... to gain the specific...
Answerer: Force.
Answerer: So I will... I'm expecting to hit the ball with that
   specific force. But yeah, compared to the VR, it's kind of light,
   so I don't know like in the field is...
Answerer: I'm missing the feeling, okay, to able to control it. Like
   what kind of force?
Questioner: Okay. So overall do you think they are helped you learn
   golf?
Questioner: A bit, a bit. Okay. Thank you.
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Interview 11 (ConClub)

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Questioner: Did you feel any discomfort in the VR environment?
Questioner: Discomfort.
Answerer: Not much, but...
Answerer: Like there was a, maybe a...
Answerer: The sound of fan in the VR that maybe... you... but...
Questioner: But if you're not that immersed.
Answerer: But not that...
Questioner: Much. Okay, right. Then it...
Answerer: Was quite comfortable.
Questioner: Okay, perfect. Then how would you describe the feelings of
    playing golf in the real world?
Answerer: Our real world, it's a bit different because...
Answerer: You...
Answerer: Okay, how do I describe?
Answerer: So in real world, since you are seeing like... you're not
   seeing your screen.
Answerer: And you have like more...
Answerer: You know more about your body, how your body is aligned.
Questioner: Yes, that's true, but...
Questioner: In...
Answerer: In VR, you don't know how your body is aligned.
Answerer: And you just see just the environment and not your body, so
   maybe a difference.
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Questioner: Okay, then how does the feedback you perceive in VR
   compared to what you are experiencing in reality?
Answerer: Sorry.
Questioner: How does the feedback you perceive in VR compare?
Answerer: Feedback from the... you mean learning basically. Okay, so I
    think it's quite helpful because...
Answerer: Initially you need to learn the terrain basically, but in
   real you could see it like more clearly. That's how it is. So. But
    once you learn, you get to know like you can do good as well,
   like...
Answerer: In VR. Okay, and that helps you actually. But when it comes
   to the power you have to apply when you are... you have to hit the
    ball, how much power you have to hit the ball, that is a bit
   different. Different, quite different. Alright. Okay, because when
    I am hitting the ball now...
Answerer: The haptics I am getting...
Answerer: Is different, and there I'm not getting any haptics, any
   feedback from the ball like when I'm hitting I'm not feeling any
   force.
Questioner: So that is makes sense.
Questioner: How do you think it would affect your performance if you
   use the real club training in the real world?
Questioner: You become better?
Answerer: I think it will... help. Help a lot because...
Answerer: It is quite better actually in... in VR like you have... you
    can get to know the...
Answerer: Learn more about the directions...
Answerer: And...
Answerer: Of course in reality you learn differently, so...
Questioner: It makes sense.
Answerer: But you will get to know correct directions basically, so
   that will help. And...
Answerer: If it is a bit more guided...
Answerer: That you can position your... like this stick more like this
   ... like then it will... it will change a lot. Okay.
Questioner: The last question, do you have any other comments about
   your experience?
Answerer: No, no, I guess.
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Interview 12 (ConClub)

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Questioner: First question, did you feel any discomfort in the VR
   environment?
Answerer: None,
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Questioner: How would you describe the feeling of playing golf in the
   real world?
Answerer: It's just... playing golf is very physical.
Questioner: How does the feedback you feel in VR compare to the
   feedback you experience in reality?
Answerer: Definitely, the clubs in VR are far inferior to real clubs.
   It feels more floaty, and there's no sense of impact when you hit
   the ball.
Questioner: Do you think training with this high-fidelity controller
   in VR has helped you adapt to the real world faster?
Answerer: No.
Questioner: If you were training...
Questioner: ...using real clubs on a real course, do you think it
   would affect your performance? Would it be better or worse than it
    is now?
Answerer: Uh, it would be better than it is now.
Questioner: So how... overall, do you think VR is helpful for learning
    golf?
Questioner: Okay.
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Interview 13 (Con)

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Questioner: Do you feel uncomfortable in the VR environment?
Answerer: After playing for a while, my waist felt a bit sore, and the
    VR headset felt a bit heavy.
Questioner: Okay, so how would you describe the feeling of playing
   golf in the real world and in VR?
Answerer: In the real world, you can really feel the weight of the
   club and the ball, and how much force you need to use. After
   playing ten balls, when I entered the VR environment, the
   controller felt too light, and I couldn't feel the weight of the
   ball.
Questioner: What do you think are the differences in the feedback you
   receive in these two environments?
Answerer: In the real world, you can't see the trajectory of all the
   balls, so you don't know unless you consciously remember whether
   your ball went left or right, or how far it went. But in the VR
   environment, you can see where your last shot landed based on the
   force you used, and whether all your shots are biased to the left
   or right.
Questioner: Feeling.
Questioner: Does using this controller affect your performance?
Answerer: Yes, because there are some buttons on it. I don't know what
    happens when I press them, so I hold it lighter. But if I hold it
    lighter, it might affect the force of my swing.
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Questioner: Okay, last question. Overall, do you think this VR has
   helped you learn golf?
Answerer: Yes, I do. I think because when I first started playing, I
   used too much force. After entering the VR environment, I realized
    how to control my force better, and the ball speed is much faster
   . So you get to practice a lot, and you can see the feedback of
   all your shots, whether they went left or right. After leaving the
    VR environment, when you're actually playing, you'll be more
   conscious of using less force, or adjusting your swing a little to
    the right.
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