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Performance Improvement and Skill Transfer in Table Tennis Through Training in Virtual Reality

Hawkar Oagaz, Breawn Schoun, and Min-Hyung Choi

Abstract—Sports professionals have been increasingly using Virtual Reality (VR) for training and assessment of skill-based sports. Yet fundamental questions about the virtue of VR training for skill-based sports remain unanswered: Can the complex motor skills required in these sports be learned in VR? If so, do these skills transfer to the real world? We have developed a VR table tennis system that incorporates customized physics with realistic audio-visual stimuli, haptics, and motion capture to enhance VR immersion and collect information about the player's posture and technique. We have assessed skill acquisition and training transfer by comparing real table tennis performance between a control group (n=7) that received no training and an experimental group (n=8) trained for five sessions in VR. Our results show a significant improvement in technique but no significant changes in the number of the returned balls in the experimental group in the real-life retention session. However, no significant differences are found in the control group. Our findings support the notion that complex skills can be learned in VR and that obtained skills can transfer to the real world. This work offers an inexpensive VR table tennis training platform, enabling effective training via real-time motor and ball returning technique feedback.

Index Terms—Virtual reality, training, motor learning, performance improvement, skill transfer

1 Introduction

Training is crucial in a variety of domains, from personal endeavors such as music and sports to professions like firefighting and nursing. VR has been researched and used for training for the past few decades for a variety of activities [1], [2], [3], such as surgery [4], [5], sports [6], [7], [8], [9], [10], [11], and navigation [12]. The draw of VR for training is not only its ability to synthesize realistic conditions when on-site training is expensive, dangerous, or difficult to replicate in real life, but also the ability to create extreme, unrealistic conditions to "over-prepare" trainees for the real situation. Full control over the visual and auditory experience of the user, as well as some control over haptic feedback, makes for an engaging training experience and ensures the reproducibility of training sessions.

There is a considerable amount of research exploring the use of VR training for sports. Endurance (closed-skill) sports such as running, cycling, and rowing have generally been the focus of these studies, as they are largely self-driven and translate well to a Virtual Environment (VE) [9], [10], [11]. Skill-based (open-skill) sports are more challenging to design due to a heavier reliance on external factors such as additional players, infrastructure, timing, and physics and have received less attention in the research literature. These sports additionally tend to involve complex motor and decision-making skills, requiring accurate real-time reactions from the player [1]. Therefore, questions remain to be answered about the efficacy of VR training for skill-based sports. Can the complex motor and decision-making skills required in these sports be learned and performed in VR? If so, do these skills transfer to the real-world activity?

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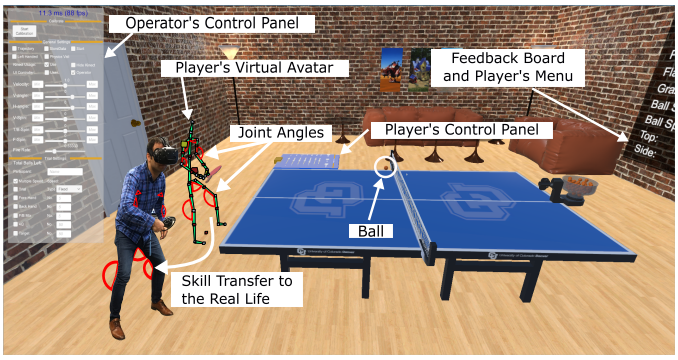

Fig. 1. The virtual table tennis environment is designed to resemble a realistic table tennis play area.

The sparse literature available yields no consensus on the answers to these questions; some research shows transfer from virtual to real-world performance, whereas some show no transfer, or even negative transfer [8], [13], [14], [15], [16].

One specific skill-based sport that has been the subject of training transfer research is table tennis [14], [17]. Learning to play table tennis is mentally demanding, requiring quick decision-making and an understanding of the physics of ball flight, collisions, and the ball-paddle relationship. However, abstract learning by itself does not automatically result in transfer to the real world; while a person may develop a theoretical understanding of table tennis through watching videos, they may not necessarily become a better table tennis player. Gamification of table tennis in VR, which requires the player to develop the mechanical ability to respond to an incoming flying ball, will likely lead to performance improvement through repetitive practice, as it combines the mental and motor aspects of learning. Still, performance improvement from gamification alone does not equate to professional training and will not prepare the player to compete at a higher level. To learn to play table

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tennis at a professional level, the participant must learn and practice the techniques of professional table tennis players and receive feedback on their technique as they train. When theoretical learning, motor learning, and effective instructions are successfully combined, it is evident in the consistent production of optimal ball flight characteristics.

Though many studies have explored training transfer in table tennis [6], [14], [17], a commonality in the methodologies of the existing literature is the lack of either informative or guidance feedback to the user, even though research has demonstrated the importance of both for motor learning [18]. Studies of training transfer for other sports have employed motion capture technologies to provide guidance feedback and analyze performance [6], [19], [20], demonstrating the power of this technology to aid in training and its potential applicability to other sports such as table tennis. Success in table tennis is largely dependent on correct player kinematics, which is normally achieved by both informative and guidance feedback from a trainer. While it is clear that the use of informative and guidance feedback could significantly impact learning and training transfer for VR table tennis, to our knowledge, no VR table tennis system exists that combines this type of guidance with realistic audio-visual stimuli to achieve correct posture and movements.

Therefore, to explore open questions of VR skill transfer regarding table tennis, we have developed a VR table tennis system that trains participants to play with proper posture and technique and assesses their performance. Users engage with a realistic table tennis VE, featuring immersive visual and audio stimuli and our own physics simulations that were validated and realistically replicate real ball flight. The individual plays using a tracked paddle similar in size, weight, and shape to a real table tennis paddle, while their movements are recorded with a depth sensor. The system provides information and guidance feedback on movements and posture and records movements and data for later analysis. Using this system, we study how participants improve their motor skills over five training sessions in the VE and if they can apply techniques learned in VR to the real-world game through quantitative and qualitative assessment.

The skill-learning process's effects can be observed in the VR system by comparing data from initial training sessions to data from later sessions. Skill transfer from VR to real life, on the other hand, is evaluated by comparing real table tennis baseline and retention assessments as shown in Figure 7. Because the VR system simulates real ball flight physics, the same techniques in virtual and real-life table tennis should produce similar ball flight characteristics. Therefore, our general hypothesis is that if the VE effectively mimics real-life table tennis training and provides effective instruction and feedback, there should be a performance improvement between data taken before the first and data taken after the last VR training sessions, and between baseline and retention real table tennis data collection sessions for those trained in the VE. This general hypothesis is based on existing literature regarding learning and training in VR, where VR training has shown improvement in skills in post-training analyses [21], [22].

We have designed an experiment that compares data from an experimental group that undergoes VR training with a control group that does not. Participants in the experimental group go through five VR training sessions (45 minutes each). Data from our professional table tennis trainer who runs a training center was instrumental in the design of our experiment. We chose five sessions because the training center data showed that modification of motor skills towards that of a professional player could be seen after this amount of time. This alteration of motor skills results in ball quality improvements, namely lower ball heights over the table and faster ball speeds. Additionally, the data showed that the number of returned balls decreases initially; according to the existing literature [21] and our table tennis trainer. This is due to players experiencing a "learning curve" where they need to adjust to a new and unfamiliar way of returning balls. After several more training sessions where posture and technique are the central focus, the number of returned balls will increase. Therefore, in our experiment, we instructed participants to focus on returning lower, faster balls as the training goal instead of getting balls across the net. These considerations were used to determine our metrics of success and to form the following hypotheses:

- H1: The number of returned balls will decrease for the experimental group in the retention session, while no significant changes will be observed for the control group.
- H2: The returned balls' speed will increase significantly for the experimental group in the retention session, while no significant changes in ball speed will be observed for the control group.
- H3: The height of the returned balls (above the table) will decrease significantly for the experimental group in the retention session, while no significant changes in ball height will be observed for the control group.

We recruited 18 participants and divided them randomly into an experimental group and a control group. The experimental group went through forehand and backhand drive returns training, while the control group did not go through any training. Data from the retention session show no significant changes in the number of returned balls but significant improvements in ball speed and height, which improved by 22.2% and 26% respectively for the experimental group. In contrast, no significant improvement is observed in the control group. We used independent-samples t-tests, paired-samples t-tests, and repeated-measures ANOVA tests to deliver statistical analysis for interpreting results. Our results are promising and support the validity of VR training for skill-based sports such as table tennis.

This study has two main contributions. First, it demonstrates the validity of skill learning and transfer in VR for sports and more broadly contributes to answering the question of performance improvement in VR. Second, this work will offer a low-cost, remotely-accessible platform for table tennis players that enables them to train more effectively with real-time feedback. It is worth mentioning that the goal of this study is to show the effectiveness of VR training and skill transfer to the real-world activity and not the effectiveness of VR training compared to real training. However, this is part of this work's future trajectory, as well as how we can use this system for more in-depth behavioral analysis during training to further understand the learning processes involved in table tennis.

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2 Related Work

VR technology has been applied to a variety of sports for performance analysis and training. One of VR's strengths over real training is the ability to create reproducible scenarios that are difficult or impossible to achieve in real life, as noted in a study exploring the use of VR as a training tool for baseball hitting [8]. In addition, motion capture technologies in VEs facilitate a more in-depth analysis of performance than traditional video playback, as demonstrated in a study that analyzed the performance of rugby and handball players in a VE [6]. Many studies in VR sports have investigated training transfer from virtual to real-world performance; results from a study in real and virtual dart-throwing suggested transferability between virtual and real [9], as have studies investigating juggling [10], rowing [11], bowling [23], and a variety of ball sports [1], [19].

Several table tennis simulations have been created in VR and Augmented Reality (AR) over the past two decades. As the fast pace of the game necessitates quick response times in VR, a few studies have explored VR setups that enable a more realistic experience through improvements in speed [24], [25]. As a two-person game, table tennis has also been investigated from the perspective of collaborative virtual entertainment [26], [27]. An early exploration of training transfer in VR table tennis found that training in VR resulted in improved real-world table tennis performance and attempted to identify key variables required for success by removing elements of the VE [14].

A recent similar work that investigated training transfer with VR table tennis was conducted by Michalski et al. [17]. They used a similar experimental setup to compare an experimental group that went through VR training with a control group that did not go through training, and significant performance improvement was observed in the experimental group. However, study participants did not receive any instruction regarding technique, nor any feedback throughout the course of training, and data was not collected during the VR training sessions. In our study, we have developed a training system that provides instructions in multiple modalities, gives real-time feedback on posture and movements, and collects detailed data for in-depth analysis. Additionally, while their real-world table tennis assessment was evaluated by a professional, our evaluation compares quantitative measurements of ball flight using computer vision techniques to analyze performance objectively without human intervention.

3 System Design

3.1 VR Table Tennis (VRTT)

Figure 2 shows the overall system design with the three fundamental components. The VRTT system was built using Unity Engine on an Alienware Area-51 R2 desktop computer with an HTC VIVE Head Mounted Display (HMD). The player holds an HTC racket with an HTC tracker mounted on the racket, which has a similar size, weight, and grip to a real racket. In the VE, the player undergoes training to imitate a virtual professional player's posture and movements and compare their own posture to that of the avatar by having their own skeletal data recorded

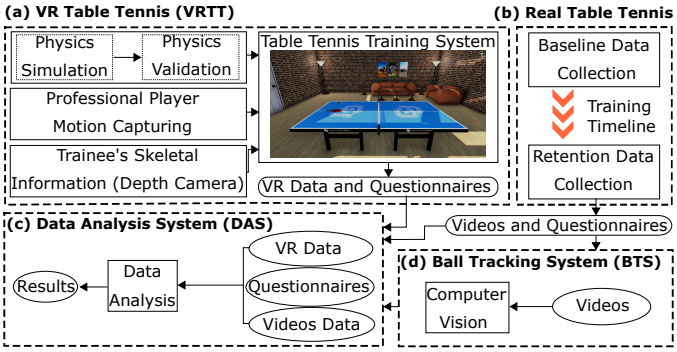

Fig. 2. Overall system design consists of the three main sub-systems, starting with VRTT and ends with DAS.

using a Microsoft Kinect 2. The player then returns balls shot from a ball shooter, practicing forehand and backhand drive techniques while maintaining correct posture. Figure 1 shows the VRTT environment. The following subsections cover the physics simulation of ball flight, creating a training avatar, and assessing the player during training.

3.1.1 Physics Simulation and Validation

Generic physics engines such as PhysX in Unity provide standard physics simulations for games and maintain a refresh rate that makes games visually realistic. Though Unity can accurately model ball flight, the rebound physics of PhysX does not have enough parameters to realistically model the spin transfer during a bounce. Because table tennis involves numerous ball collisions, the collisions need to be as accurate as possible to offer a near real-world experience. Also, Unity physics lacks complicated and critical phenomena such as the Magnus effect. Therefore, we have developed our own physics simulation that is specifically designed to overcome these limitations. The flight of the ball and its rebound off the paddle and the table use a realistic physics model, where the ball loses energy when rebounding, spin is imparted to the ball from friction with the rebound surface, and gravity, air drag, and Magnus forces affect the free flight of the ball. We use a prediction system to detect the ball's exact collision point and its surrounding objects, including the table and the paddle. Though our chosen hardware has framerate limitations (HTC Vive lighthouses have a tracking sweep rate of 60 FPS, and the headset refresh rate is 90 FPS), the framerate is still enough to provide a realistic experience for beginners, which is our target population. In this paper, we will focus on the validation of physics simulation of the ball flight.

To validate our physics simulation, we devised a method to compare real ball and VR ball flights. To do this, we used a ball launcher with predefined settings to create reproducible ball flight scenarios and used computer vision (OpenCV in Python) to track and analyze the flight path and speed of a real ball. We used this information to replicate ball behavior in VR and compared our simulation to real-life ball flight.

a) Setup

The two most important aspects of our physics simulation are determining correct ball speed and trajectory. To calculate the speed correctly in real table tennis, there should be a physical known distance to compare the ball position over time. Figure 3 shows our physics validation

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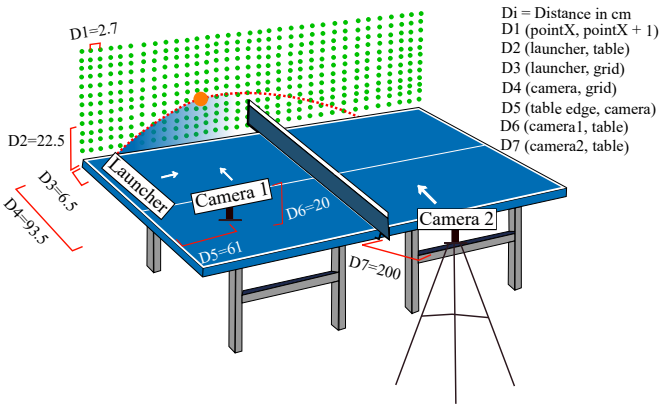

Fig. 3. Physics validation setup consists of a dotted green board, two high-speed, high-resolution cameras, and a ball launcher.

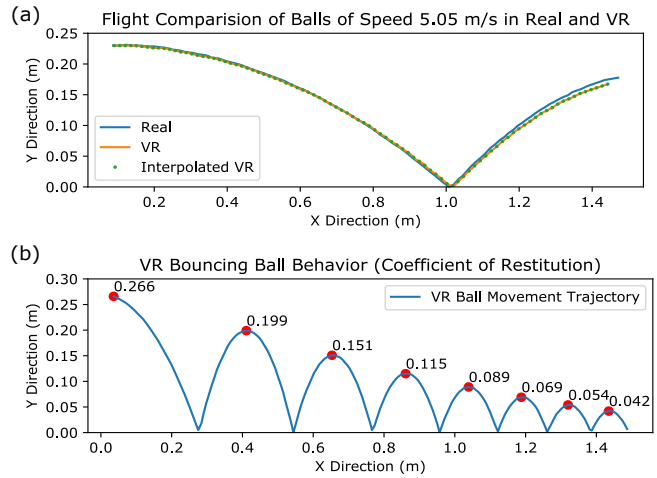

Fig. 4. Physics validation results. (a) shows the ball flight comparison in real-world and VR simulation (VR sequence is interpolated for the comparison). (b) shows ball bouncing behavior in VR.

setup where a ball launcher shoots balls at different speeds while being recorded by two cameras running at 240 FPS with 1080p resolution. One camera views the ball from a close distance to better determine the exact ball position. The other camera views the ball from a further distance to determine the ball's trajectory. A grid of green dots on a whiteboard was placed behind the table so that the ball flies in front of the board when launched. By knowing the distance between dots (2.74 cm), we used computer vision techniques to determine the ball position's change relative to the dots to determine its speed and trajectory. To test our setup, balls with speeds varying from 4.39 m/s to 6.46 m/s were shot from the ball launcher and recorded. Since spin is not validated, we reduced the spin to the minimum. In the launcher control board, ball speed and spin are coupled; higher speed means higher spin. However, as long as both topspin and sidespin are set to be equal, the ball trajectory deviation is minimal, and the ball behaves as though it has minimum spin or no spin at all.

b) Evaluation

To evaluate how closely our physics can simulate real ball flight, we took the speed calculated from the close camera and fed that to the virtual launcher. We then compared the ball's trajectory as determined from the further camera to the ball's trajectory in the VRTT system. We used Dynamic Time Warping (DTW) to score the similarities in the ball trajectory between both sequences [28]. The Euclidean distance of DTW of the two sequences is between 2 m - 2.5 m, and the normalized score is 0.01255 - 0.00734. To show how similar these two numbers are, we compared two consecutive real balls, and the DTW distance was 1.03884 m with a normalized score of 0.00577. This is because it is almost impossible to generate an exact trajectory in the real world due to many factors affecting the trajectory, such as launcher inconsistency launcher and air drag. Also, small shifts between points will result in some differences even if the sequences are similar. Therefore we can conclude that having a normalized DTW score between 0.01255 and 0.00734 is very similar and is comparable to what the real ball launcher can generate. Figure 4a shows the ball trajectories of both real and VR data.

While DTW validates the ball flight, it doesn't tell us what happens during ball collisions. To validate the ball's collision behavior, another experiment was conducted in VR to test the coefficient of restitution. According to the International Table Tennis Federation (ITTF) [29], the playing surface of the table tennis table needs to cause the ball to bounce approximately 23 cm when it is dropped from a height of 30 cm (approximately 76.6%). We dropped the ball in VR on the table and evaluated seven bounces to show that the ball precisely loses energy at each collision. Figure 4b shows the average of bouncing is 76.68% which represents an accuracy of 99.76%. These results illustrate a very realistic ball behavior where the ball loses energy after each collision based on the incoming force, ball speed, and the collided object's physical material.

For a qualitative assessment of our ball flight simulation, we consulted our professional trainer, who has previously won the Colorado State Table Tennis Championship, to test the system. He has over 25 years of experience and an exemplary understanding of rules, postures, and ball flight physics. His feedback was positive about the behavior of the ball, further validating our physics implementation.

3.1.2 Motion Capturing

Correct posture is of critical importance for table tennis training. To guide trainees, we have created reference measurements and a feedback system based on a professional player's (the trainer's) motion capture. We used a Vicon motion system with 20 cameras to record the professional trainer's movements doing basic forehand and backhand motions. We then created a VR animation to teach participants the right postures and movements.

3.1.3 Training system

The training system can be divided into two parts: posture training and ball returning training. For the posture training setup, the depth camera is used to capture the player's skeletal information while playing VR table tennis. The depth camera data is used to indicate if the player is performing the correct movements in real-time by comparing it to the professional avatar, and in post-processing to analyze the player's behavior. In this study, we focused on basic performance improvement techniques advised in real training settings for beginner and intermediate-level

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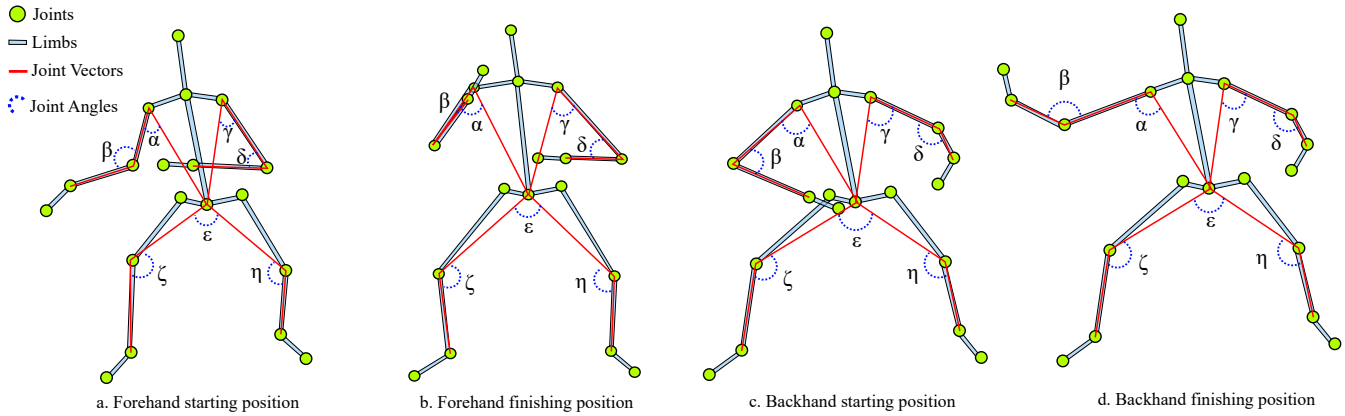

Fig. 5. Posture training model. The angles between joint vectors of body extremities determine if the user performs the correct posture.

trainees. Instructions for these techniques are presented on a virtual feedback board in front of the participants in the VE so that they are able to follow along with the instructions.

We focus on six practices and habits to help the participants improve their performance: (1) Posture: The player needs to be in a squatting position with their torso forward and their weight on the balls of their feet. When the player rests their hands on their thighs, their hands should be at the same level as the table. (2) Paddle holding: The paddle hand should be in a straight line with the arm (no bend at the wrist). The index finger should point towards the ground. (3) Elbow position: In the forehand drive, the player's palm should face the table, and the forearm should be parallel with the table. The forearm can be rotated towards the table to produce greater ball spin. The elbow should make an approximately 45-degree angle relative to the torso. In the backhand drive, the back of the hand should face the table, the forearm should be parallel with the table and rotated towards the table, and the elbow position should be out. (4) Starting point of the hand motion: The paddle motion starting point should be low to avoid extra effort when returning the ball. (5) Arm movement: Forehand drive movement starts when the hand is parallel with the table and driven by the hips' rotation—the hand curls at approximately 45 degrees. At the end of the arm movement, the hand should be in front of the player's head. In the backhand drive, the hand movement starts between the legs, and the arm moves upward, rotating about the elbow. (6) Timing: The player should wait until the ball is between them and the table before starting arm movement.

The listed instructions are presented to the player in text, pictures, and animations provided by our professional trainer. Figure 5 shows the starting and finishing positions for forehand and backhand drives. The joint angles of both the avatar and player's skeletal data are compared in real-time to assess similarities between postures. α, β, γ, and δ angles represent the upper-body posture while ϵ, ζ, and η represent the lower-body posture. At each time step, the joint angles are taken from the depth camera and compared to the avatar's joint angles to indicate if the player is performing the movements correctly. A 10-degree error window in each direction is used for comparison.

Three indicators are used as feedback to the player to indicate whether or not they are achieving correct posture: leg posture (squatting), arm posture (striking), and combined posture. Indicators in the VE are green when the player achieves correct posture and red when posture is incorrect. The angle values and indicators are shown on the feedback board so the user can see the status of their movements and adjust accordingly. The player is asked to start the motion (forehand or backhand) when the avatar starts and then follow the avatar's movements until the cycle ends. The player can choose to practice forehand or backhand by selecting the intended movement on the feedback board. Additionally, the player can observe the avatar in front of them or bring the avatar to where they stand and mirror the movements. A left-handed option is also available to the players, which mirrors the animation and angle calculations.

In the ball returning training, the player is trained to play table tennis by returning balls fired by a VE ball launcher. The ball launcher is a simulation of a Huipang HP-07 table tennis dispenser, the dispenser used for the real-life assessment. This launcher can provide four different ball spins (topspin, backspin, left sidespin, and right sidespin) and various spin combinations. The spin, ball frequency, speed, and launching angle are controlled to provide a realistic VR experience. As an alternative to the launcher, a robotic opponent is implemented to give the player a similar experience to real-world table tennis.

The launcher can shoot balls in all variable combinations that our physical launcher can offer and many other options that the physical launcher cannot. In contrast, the opponent (represented by a paddle) is designed to offer very realistic conditions. The robot can serve and return the ball like a professional player and send the ball with or without spin and in any direction. The ball speed can also be configured to match the player's level. The player has full control over both the launcher and the opponent configurations. Furthermore, the researcher or operator can change the configuration using a control panel on the screen to generate specific training scenarios.

There is a set of the predefined ball returning scenarios that the player can choose from. Each of these options targets a particular skill. These settings include forehand, backhand, and mixed returning (a combination of forehand and backhand). Additionally, the player can choose to add a target to the table to practice returning in a particular direction. For target exercise, the far side of the table can be divided into two or four equal parts or a user-specified number of targets can be placed at the edge of the table.

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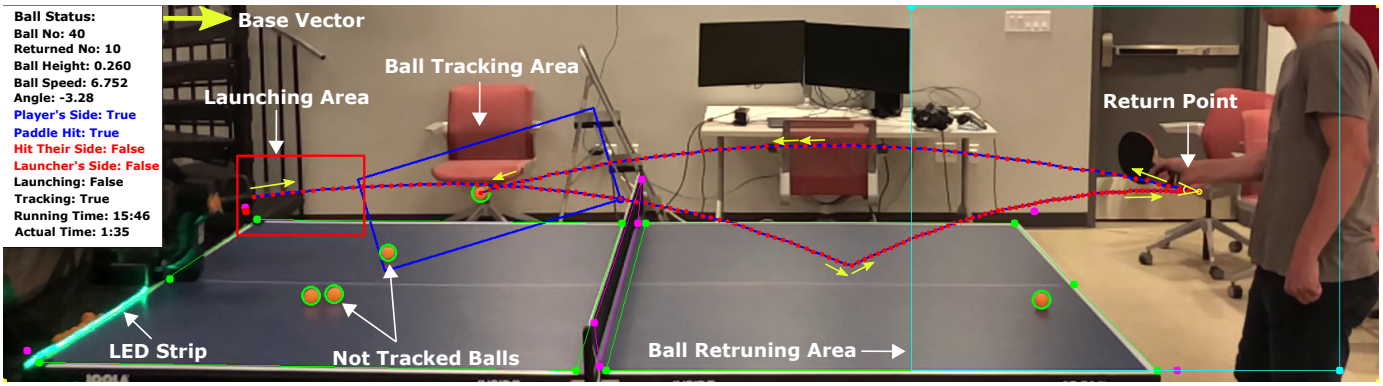

Fig. 6. Ball Tracking System (BTS) tracks the intended ball in the videos taken in real-world assessment data collection.

3.2 Ball Tracking System (BTS)

A Ball Tracking System (BTS) using OpenCV (in Python) was developed to generate the data needed from videos taken during data collection sessions. Using this system, we evaluated videos from the baseline and retention sessions to assess participants' performance. The collected data includes the number of returned balls and ball characteristics such as speed, height, return angle, and collision points.

Tracking the correct ball is a challenging task in the training setup since there could be multiple balls on the table and in the scene. 50 balls are shot for each trial, leading to a high probability that many moving balls will be in the scene at once. Additionally, balls are tracked based on shape and color, and varying lighting conditions can make the ball difficult to track. Therefore, we developed a robust ball tracking system that works even in challenging lighting conditions and despite how many balls are in the scene.

Figure 6 shows the system and the setup. Two cameras, one with a framerate of 240 FPS and one running at 60 FPS, recorded participants as they played. We attempted to place the cameras at the same positions and angles for all the participants for both baseline and retention sessions, but this proved to be difficult using tripods. Therefore, we selected regions of interest (ROIs) in the videos manually during processing. Important ROIs include the table (launcher's side and player's side separately), the net, the launcher nozzle, the launcher area, and the player returning area.

There are fundamental rules that need to be implemented to track the right ball when there are many balls in the scene. Ball registering regions are restricted to two areas: the launching area and the tracking area. As shown in Figure 6, the launching area covers the area surrounding the launcher nozzle, from which every new ball originates. The tracking area is the area around the flying ball. After determining these two areas in the video, we set rules to pick which ball to track. A base vector that goes from the left side of the video frames to the right side is used to calculate the ball trajectory during flight. The difference between two consecutive ball trajectory vectors is used to calculate relative ball trajectory changes.

Balls exiting the launcher initially travel forward and slightly upward. When the ball is above launching level, the ball's delta distance should be approximately average (as calculated from the first ball launched), and the flying angle shouldn't change drastically. These rules ignore balls returned from the opposite direction or balls that bounce in the launching area. Once a new ball is detected, the ball's surrounding area is considered a tracking area. When there are multiple balls in the tracking area, the best-suited ball is selected based on a ranking system that takes distance, change in angle, previous ball direction, amount of change, and area position into account. Additional rules regarding angle of approach and return are also used to track the ball. When multiple balls satisfy the tracking criteria, each ball's history is considered to pick the right one.

The system calculates the ball speed, ball height above the table, return point, and trajectory. Because the ball varies in speed and height for each frame, we measured the average ball speed and height from when the paddle hits the ball until the ball hits the table for successful returns. Since we are not using the board with green dots for this system, we used the table's length (2.74 m) to convert pixels to meters and determine the speed and height of the ball. Then, the generated data was fed to the Data Analysis System (DAS).

3.3 Data Analysis System (DAS)

Collected data were analyzed using the Data Analysis System (DAS). As shown in Figure 2, we have three data sources: VR data, real data, and questionnaires. This Python-based system analyzes and displays data based on selected categories and variables. The operator can select the data set (real, VR or questionnaire), group (experimental vs. control), data axes base (subjects vs. trials), population (group vs. individual), and measurement (ball count, ball speed, ball height, angle, collision points). For example, the operator can choose to see the experimental group's improvement for all subjects or select an individual subject. They can view the same data from the trial perspective to see which subjects performed better or worse during a trial or based on a specific measurement. Overall, this system provides an easy and effective way to understand and analyze the data.

4 Experimental Design

Before recruiting subjects, we obtained approval from the Institutional Review Board (IRB) of the University of Colorado Denver for this study. 18 subjects (5 females and 13 males) with no table tennis experience were recruited on campus through flyers and email advertising. All participants were between the ages of 18 to 32 years old. One participant was left-handed, and the rest were right-handed.

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Participants were randomly divided into an experimental group and a control group (9 subjects per group). Before the data collection, participants signed a consent form which explained the experiment in detail, including benefits and risks of the study and inclusion and exclusion criteria. The subjects had to have no experience in table tennis and not be active in any ball-handling sports. This was intended to eliminate other variables that may contribute to performance improvement. As shown in Figure 7, both groups went through baseline data collection, which took approximately 2 weeks to complete. After finishing the baseline data collection, the experimental group went through 5 VR training sessions that lasted 45 minutes each. We collected data in the first VR assessment session (A1) before the first VR training session and after the fifth VR session in the fifth VR assessment (A5). The control group did not take part in any training. The VR training phase took around 3 weeks to complete. After completing VR training, both groups went through a retention data collection that took 2 weeks to complete. Collected data included videos, VR data (for experimental group), and questionnaires.

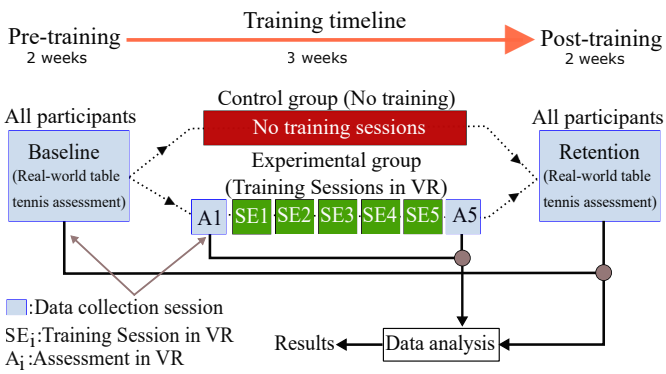

Fig. 7. Experimental design of the study.

4.1 Real Table Tennis Data Collection

Baseline and retention data collection sessions were designed to measure the participants' ability to return balls in different scenarios to assess their consistency and performance. VR training aims to train the participants to return balls at a faster speed and lower height. The experiment consisted of 4 different trials: forehand, backhand, mixed and targeted. The first two trials require the participant to return balls using solely forehand or backhand maneuvers, respectively. In mixed returning, the launcher nozzle alternates between the left and right sides of the table, requiring both forehand and backhand returns. Targeted returning adds onto mixed returning by requiring the participant to return balls to a particular side of the table, as indicated by two LED light strips affixed to the left and right sides of the table's far edge (see Figure 6). A Raspberry Pi controlled the two LED strips, randomly choosing which side to turn on. The lights on the targeted side were turned on when the ball was launched, and only balls that hit the lit side counted as hits. While the first two trials largely emphasize the participant's motor abilities, the mixed trial adds cognitive load by requiring the participant to choose between forehand and backhand. The targeted trial challenges both the participants' motor and cognitive skills.

The participants used a recreational paddle during assessment trials. Each trial was done at two different speeds, referred to as speed A (4.4 m/s) and speed B (6.5 m/s). This means that for each data collection, participants went through 8 trials. For each of the 8 trials, 50 balls were shot from the launcher; we used this number of balls (in total, 400 balls for each subject) to have enough data to judge the performance. During the baseline and retention data collection sessions, the participants were videotaped using two cameras, one with a slow-motion 240 FPS camera and a backup camera running at 60 FPS (for comparison purposes). Additionally, we counted the number of hit balls manually. Videos and the manually counted hit balls were used later as input to the Ball Tracking System (BTS). To assess each subject's progress, we compared each phase's measurements after the retention data collection session. We examined the subject's success rate, observed their recorded movements while playing, and compared their questionnaire answers from each phase.

4.2 VR Table Tennis Data Collection

At the beginning of each session, a depth camera was placed in front of the player and calibrated to the VR scene to align the player's skeleton with the table in the VE. Each session started by asking the participants to wear the VR headset and read the instructions shown on VE's feedback board. They were then asked to try forehand and backhand postures until they mastered the posture's starting and finishing movements by mimicking the professional avatar. During training, the lead researcher guided the participants on using the system and made sure they were comfortable using the VR headset for the training period. The researcher occasionally gave feedback regarding instructions and posture. After practicing the basic forehand and backhand movements, participants went through forehand, backhand, mixed, and targeted ball training sessions. During the 4th VR training session, the participants were asked to play with the opponent and were asked to use an HTC VIVE controller that provides haptic feedback instead of the racket. The purpose of this was to collect subjective qualitative data on haptic feedback in contrast with a natural grip.

4.3 Questionnaire

We designed a questionnaire with 18 questions to collect subjective quantitative and qualitative data from the participants. The first seven questions involved a self-assessment of their table tennis skills and competitiveness. The other 11 questions were related to the VR system, such as the realism of the physics simulation, visuals, haptics, and auditory feedback. Answers to each question were rated using a Likert scale from 1 to 5, where 1 is least satisfied, and 5 is very satisfied. Additionally, we asked the participants to provide their opinions in a written form for each survey question. We surveyed all participants in both baseline and retention sessions after data collection. We also surveyed the experimental group after the first and the fifth VR assessment sessions.

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5 Results

5.1 VR Table Tennis Results

The presented data throughout the Results section met the assumptions of normality and homogeneity of variances for parametric statistical analysis to be conducted. Therefore, independent-samples (or unpaired-samples) t-tests, paired-samples t-tests, and repeated-measures ANOVA tests were conducted when needed. A set of within-subjects paired-samples t-tests is conducted for VR data (experimental group only). The results show that all participants returned fewer balls after the fifth VR session. Overall there was a 33.9% decrease in returned ball number between the A1 session (M = 25.71, SD = 7.32) and A5 session (M = 17, SD = 6.39); $t(7)$ = 2.59, p = .035. However, ball return quality significantly improved. Paddle speed increased from (M = 1.8 m/s, SD = 0.33) to (M = 3.62, SD = 0.64); $t(7)$ = -6.65, $p <$ .001, which is a 101.1% improvement. Ball speed increased from (M = 6.13 m/s, SD = 0.62) to (M = 8.73, SD = 0.92); $t(7)$ = -6.13, $p <$ .001, which is a 42.4% improvement. The average ball height over the table surface decreased from (M = 0.33 m, SD = 0.097) to (M = 0.18, SD = 0.03); $t(7)$ = 4.34, $p <$ .05, which is an improvement of 45.5%. The greatest improvement was in ball spin, which increased by 103.77% from (M = 1.59 radians/s, SD = 0.53) to (M = 3.24, SD = 0.99); $t(7)$ = -4.27, $p <$ .001. A player's ability to add spin to the ball is an important aspect of training, as will be shown in overall qualitative results. The data also shows technique improvement in terms of posture and angle of returned balls. Overall, these results fit with our expectation that participants in the experimental group would go through a learning curve, initially resulting in fewer returned balls but improved quality of returns.

Questions 8 to 18 in the questionnaire asked the participants to rate different aspects of the VR system. We used their ratings to calculate a score that represents their overall satisfaction with the VR system. Questionnaire results after the first VR session show a satisfaction level of 4.18 points out of 5. The level of satisfaction increased by 7.2% from pre-training (M = 4.18, SD = 0.47) and post-training (M = 4.48, SD = 0.27); $t(7)$ = -1.55, p = .164. Although this is not a significant change, these results show that the system can offer a good training experience from the users' perspective.

Additionally, comments were encouraging and positive regarding the system's physics, graphics, auditory feedback, and training outcomes. Some samples of the comments include: *"The ball flight and physics appeared natural to me."*, *"I felt deeply involved, the environment felt mostly realistic, and I felt that I could control the paddle accurately."*, *"The sound of the ball helped me focus on getting the timing of my swing correct"*, *"I feel like the auditory feedback compensates for the lack of haptic feedback."*, *"I learned the body position and how to hold the paddle."*, *"I feel more confident in my skills and overall improvement. Hand-eye coordination is better. Consistent returns and posture techniques helped my overall play-style."*, *"The lack of distraction in the VE was very helpful."*, and *"I feel that I have improved greatly."* Comments regarding system shortcomings were mostly related to technological limitations, such as: *"The only improvements I think would benefit are a larger Field Of View (FOV) and improved haptic feedback."*, *"The cord was distracting."*, and *"Lacking peripheral vision made it harder to know if I am going to return the ball."*.

Both satisfactory performance scores and participant comments show that our system provides an experiential learning experience that seems to positively impact their ability to play virtual table tennis. The presented data also shows that a positive learning process took place between the first and fifth sessions. Overall, the data supports that the participants gained the cognitive and motor skills required for virtual table tennis.

5.2 Real Table Tennis Results

Due to technical difficulties, two participants were not recorded at 240 FPS in the baseline data collection, and were

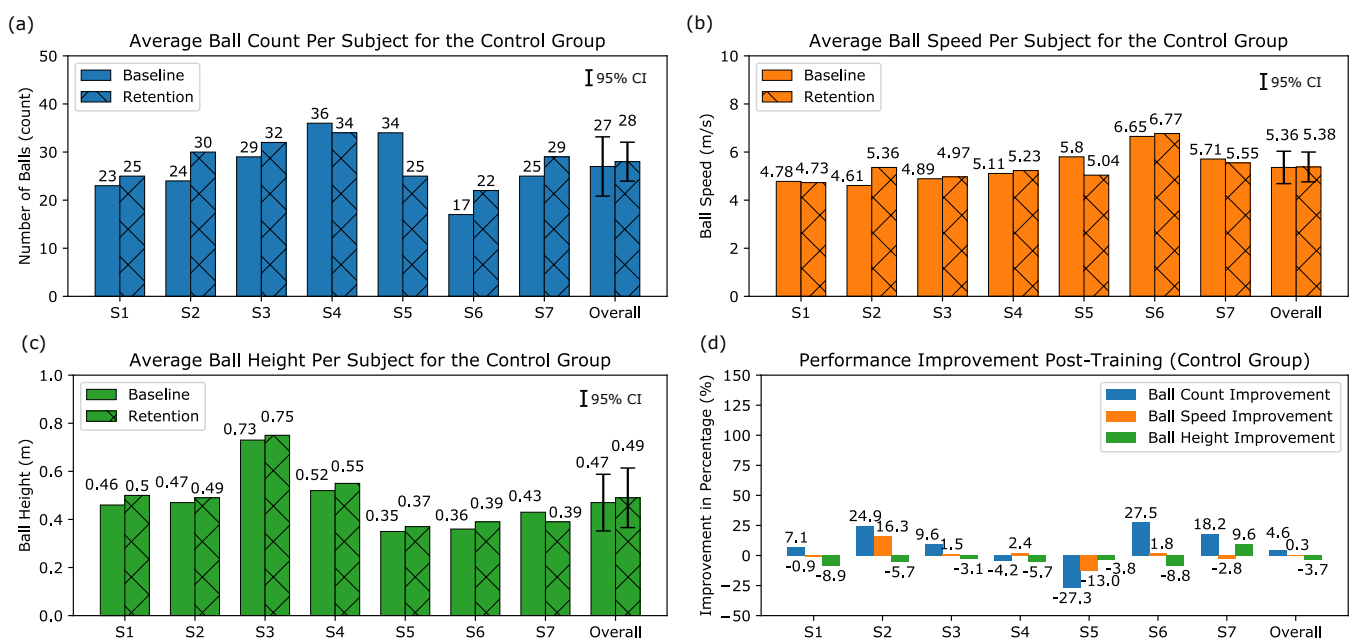

Fig. 8. Comparison of the three main measurements (returned ball counts, ball speed and ball height) between baseline and retention sessions per subject for the control group. (a) ball counts, (b) ball speed (c) average ball height, and (d) performance improvement.

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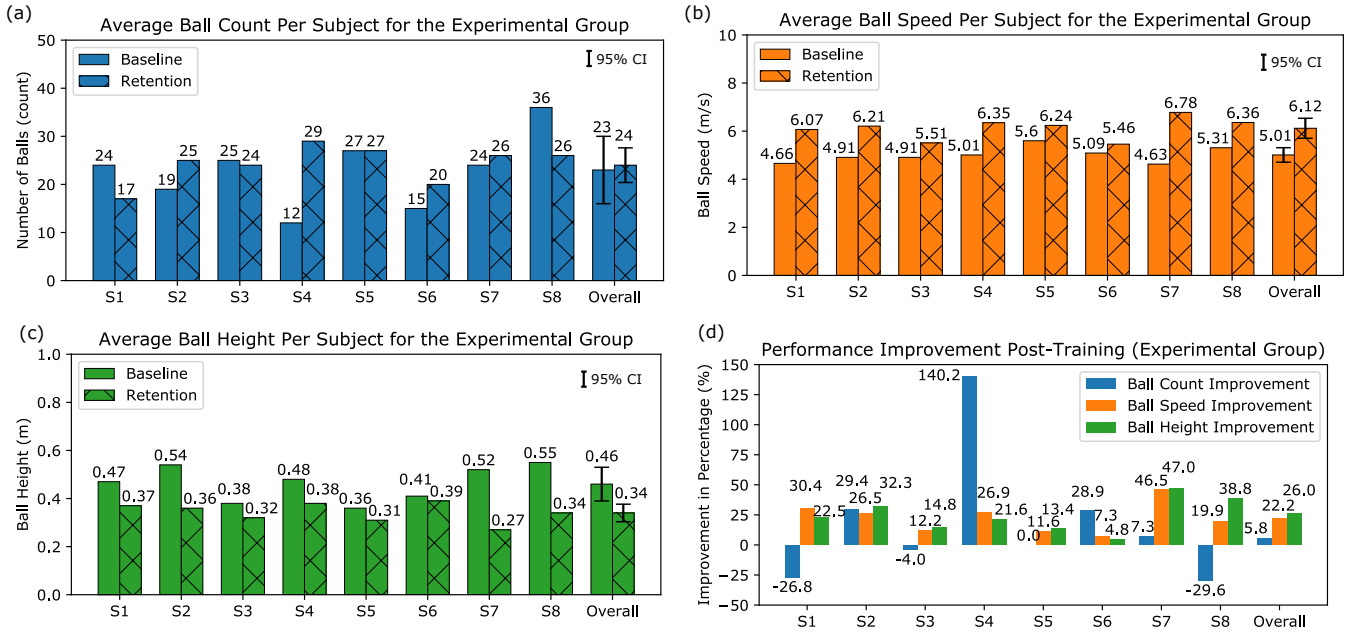

Fig. 9. Comparison of the three main measurements (returned ball counts, ball speed and ball height) between baseline and retention sessions per subject for the experimental group. (a) ball counts, (b) ball speed (c) average ball height, and (d) performance improvement.

not included in data analysis. Another participant from the control group was considered an outlier due to their active participation in other sports, as we had requested that participants not play table tennis and/or be active in another sport during the study. After removing these three participants from the study, 8 subjects from the experimental group and 7 subjects from the control group remained. The data presentation follows the hypotheses mentioned in the introduction section.

5.2.1 Data Presentation

Figure 8 displays results for the control group. Subfigure (a) shows average ball return counts for each subject across all 8 trials and the average of the whole group as overall counts. Subfigure (b) shows the ball speed across all 8 trials and overall ball speed for the whole group. Subfigure (c) shows the average ball height over the surface of the table. Subfigure (d) shows the improvement of each of the aforementioned measurements. Figure 9 displays the same information as Figure 8, but for the experimental group.

5.2.2 Hypotheses Testing

Figure 10 shows the overall training effect on the experimental group compared to the control group. Visually, we can see noticeable differences between both groups. The error bars that represent 95% Confidence Interval (CI) are overlapping in the baseline data which is a clue that there is no significant difference. In contrast, in the retention data the error bars do not overlap for ball quality indicating a significant difference. In addition to randomly assigning participants to the groups, a set of between-subjects independent-samples t-tests was conducted for the baseline data to make sure there is no significant difference between both groups before the training. The statistical tests were conducted for returned ball count, ball speed and ball height. A significance level of .05 was chosen for all statistical analysis.

There was no significant difference in the returned ball count scores for control (M = 26.82, SD = 6.65) and experimental (M = 22.73, SD = 7.48) groups; $t(13)$ = -1.11, p = .287. These results fail to reject the null hypothesis that there is no difference in the number of returned balls between groups. There was no significant difference in the ball speed scores for control (M = 5.36 m/s, SD = 0.73) and experimental (M = 5.01, SD = 0.32) groups; $t(13)$ = -1.239, p = .237. There was no significant difference in the ball height scores for control (M = 0.47 m, SD = 0.18) and experimental (M = 0.46, SD = 0.07) groups; $t(13)$ = -0.187, p = .855. The results from the three t-tests suggest that both control and experimental groups in the baseline session came from the same population.

After the retention session, three tests of one-way repeated-measures ANOVA were conducted to test the hypotheses; for each of the tests, the within-subjects factor is "training" (or time), and the between-subjects factor is "groups" (control and experimental). No significant training effect was found on the number of returned balls, Wilks' Lambda = 0.964, $F(1,13)$ = 0.487, p = .497, η_p^2 = .036. There was no significant interaction effect between training and groups, Wilks' Lambda = 1.000 , $F(1,13)$ = 0.001, p = .980, $\eta_p^2 < .001$ (see Figure 10a for the means and error bars). Visually, we can see that both groups' error bars are intersecting both in baseline and retention, meaning that there is no significant difference. These results reject the part of H1 about the number of returned balls decreasing for the experimental group (explained in the Discussion section) and support the part of H1 about the number of returned balls not changing significantly for the control group.

There was a significant effect of training on the ball speed, Wilks' Lambda = 0.425, $F(1,13)$ = 17.620, p = .001, η_p^2 = .575. When there is a significant difference, posthoc analysis is needed to show where the differences are located if there are more than two dependent variables (data points). However, in our case, we only have two data points

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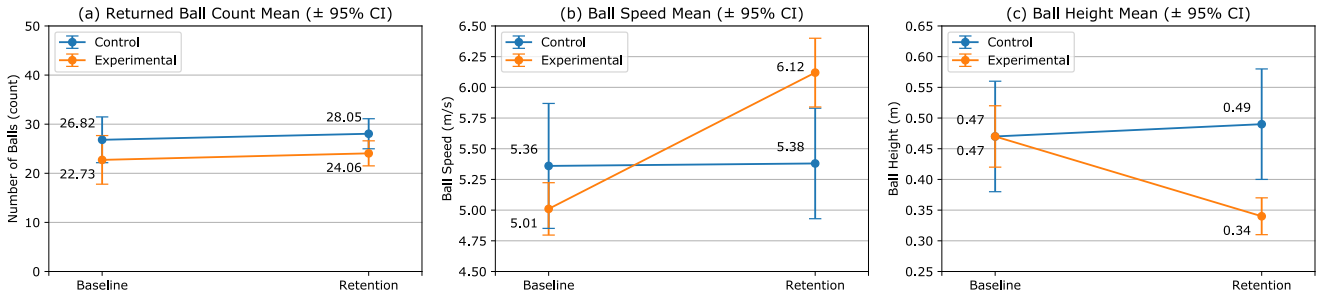

Fig. 10. Summary of the overall training effect on the experimental group's performance compared to the control group's performance.

(baseline and retention), and therefore, we can infer that the difference is between baseline and retention. Also, there was a significant interaction effect between training and groups, Wilks' Lambda = 0.438, $F(1,13) = 16.702$, $p = .001$, $\eta_p^2 = .562$. Similarly, these results suggest a significant difference in ball speed post-training between the control and experimental groups, as shown in Figure 10a and support H2 (notice the error bars intersections).

There was a significant effect of training on the ball height, Wilks' Lambda = 0.564, $F(1,13) = 10.034$, $p = .007$, $\eta_p^2 = .436$. These results show a significant difference in ball height between baseline and retention sessions. Also, there was a significant interaction effect between training and groups, Wilks' Lambda = 0.418, $F(1,13) = 18.072$, $p < .001$, $\eta_p^2 = .582$. These results suggest a significant difference in ball height post-training between the control and experimental groups (see Figure 10c) and support H3.

Additionally, the results from the first seven questions in the questionnaire regarding the participants' confidence level increased from 2.77 points in the baseline session to 3.71 points in the retention session for the experimental group, which is a 34% increase. In comparison, the control group's confidence level increased from 2.56 points in baseline to 2.82 points in the retention session, representing a 10% increase. A one-way repeated-measures ANOVA was conducted to compare the effect of the training (time factor between both data collection points) on the confidence level. There was a significant effect of training (including time) on the confidence level, Wilks' Lambda = 0.613, $F(1,13) = 8.224$, $p = .013$, $\eta_p^2 = .387$. However, these results don't show any significant interaction effect between training and groups, Wilks' Lambda = 0.826, $F(1,13) = 2.784$, $p = .121$, $\eta_p^2 = .174$. To better understand these results, we also conducted within-subjects paired-samples t-tests for before and after training. There was a significant difference in the scores for the experimental group before ($M = 2.77$, $SD = 0.62$) and after ($M = 3.71$, $SD = 0.55$) the study; $t(7) = -3.99$, $p = .005$. However, there was no significant difference in the scores for the control group before ($M = 2.56$, $SD = 0.66$) and after ($M = 2.82$, $SD = 0.63$) the study; $t(6) = -0.71$, $p = .504$. While there was no significant interaction effect between training and groups, the marginal p-value for exploratory analysis and the significant main effect between training and confidence indicate the presence of a difference in the confidence level by training. The subjective aspect of questionnaire answers and the time between baseline and retention sessions might have impacted the survey results.

Overall, the quantitative data show significant improvements in ball return quality by the experimental group after training in VR, while no improvement is observed in the control group. In addition, the qualitative feedback from the experimental group is positive and encouraging. The results show promising outcomes of our system and support the notion that skills learned in VR can transfer to real life.

6 Discussion

Though the results show significant improvement in the quality of the returned balls in virtual and real table tennis by the experimental group, further investigation is required to determine the variables that contribute most to performance improvement. It seems reasonable that closely matching stimuli between the virtual and real activity, such as we have done by replicating realistic physics and audio stimuli, would yield better outcomes, as moving from the virtual to the real task would require little to no cognitive or motor adaptation. Effective training instructions also play a role in performance improvement. Optimal posture and technique are not inherently obvious to beginners, resulting in a more ping-pong style of playing. The interplay of all of the variables in our system have produced promising results, but are any of these variables more important than the others? Conversely, are any less important, or even unnecessary? Isolating each of the variables at play would illuminate the key factors required for effective VR table tennis training, and more broadly, provide insight into the necessary conditions for VR training itself. This is something we would like to explore in the future.

We had hypothesized in H1 that the number of returned balls in the retention session would be less than in the baseline session for the experimental group because participants would go through a learning curve. Contrary to our hypothesis, the results showed that the experimental group had no significant changes in returned balls between the baseline and retention sessions. Notably, there is a decrease in returned balls between the first and fifth VR assessments. These results may be due to a slightly better paddle rubber quality in VR than the real paddle rubber, which may have over-prepared participants during VR training. A higher-quality rubber creates more ball spin than a lower-quality rubber, making ball returns more challenging. One participant commented on the difficulty of VR training compared to real table tennis, writing, *"The spin was harder in VR than the real one which made the real one easier after the training."*.

We should note that we did not validate ball spin separately due to hardware limitations. Ball launchers (including the Huipang HP-07) are not consistent enough in the

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amount of spin produced in each ball launch. Additionally, setting the parameters manually leads to inconsistent outcomes, which was the case during the physics validation setup. The spin implementation is based on equations of known forces acting on the ball rather than observed behavior by comparing with real-world data. Spin is crucial and directly affects the ball's trajectory and its collision behavior. Therefore, from the accurate physics validation results shown in Figure 4 we can infer the spin's correctness.Any inaccuracy in the spin simulation would have made the ball trajectory and collision behavior unrealistic. Nevertheless, a camera with a fast framerate and a consistent ball launcher can be used to validate the spin.

As expected, the number of returned balls for the experimental group didn't increase as much as the returned balls' quality. According to our professional trainer, participants are still considered beginners after five sessions and have not had enough training to observe improved consistency in the number of returned balls. Additionally, the launcher placement and inconsistency of ball shooting may have affected the returned balls' quantitative results. Therefore, per the study goal, we consider the ball quality more important than the number of returned balls.

The HTC VIVE paddle's inability to provide haptic feedback is a limitation of our system. Though we could have used an HTC controller, which vibrates to provide a coarse tactile experience, the controller's haptic feedback differs considerably from a real ball impact, creating a tactile mismatch between what is felt and seen in the virtual environment. We attempted to compensate for this by providing realistic auditory feedback. Another limitation is the weight distribution of the HTC VIVE paddle and tracker, which doesn't resemble the real paddle's weight distribution. In the future, both haptic feedback and weight distribution must be addressed to replicate the real conditions to reduce the possibility of any negative performance transfer.

Another limitation of the system is the framerate of the Kinect, as it only offers a 30 FPS frame rate. High-speed skeletal tracking was not the Kinect's intended purpose in development, and therefore the framerate limitation presents challenges in high-speed games such as table tennis. Additionally, tracking problems may occur depending on the participant's clothing and body orientation. However, for purposes of training beginner players that move more slowly than professionals, the Kinect serves its purpose [30]. Training beyond a beginner level will require hardware that can handle high-speed movements.

We recognize that the lead researcher's feedback during training may have added some bias, yet it was essential to ensure that system was used correctly. The feedback focused on clarifying instructions when the participants had problems understanding the variety of information provided in the virtual environment—for example, answering questions regarding instructions on how to perform forehand and backhand movements. However, because the researcher only had one professional training session, we consider the bias negligible. Having a third group trained with real table tennis to compare with the VR system would have eliminated this factor. We plan to add a new group in future work and use this system to investigate skill transfer related to behavior, decision-making, and hand-eye coordination.

One of the challenges of using VR with an HMD for training is depth perception and distance underestimation [3], [7], [15], [19]. Accurately simulating 3D realities on 2D screens is quite complicated and a known phenomenon. This problem is more evident with fast-paced activities such as table tennis. However, due to relatively small table tennis distances (standard table tennis is 2.74m) and our accurate physics simulation, this problem wasn't apparent, and participant feedback was positive regarding their ability to determine the ball's position and react in a timely manner.

The sample size dictates how we can confidently interpret the results of this study. Therefore, to validate the sample size, we performed post hoc statistical power analysis based on an alpha level of .05 for within-between interaction for each measurement using Gpower software. The observed power for returned balls count was .05, for ball speed was .965, for ball height was .975, and for the questionnaire was .336. We used the recommended power level of .80 to interpret the results. The models for ball speed and ball height were sufficiently powered. In contrast, the ball count and questionnaire models were underpowered, introducing the need for a larger sample size to contend with potential Type I error. As presented in Figures 8 and 9, the descriptive results of returned balls count are very similar; therefore, the confidence level is low for the findings' generalizability. Similarly, because of the subjective survey nature, a higher power is needed for more confident interpretations. In contrast, the power for both ball speed and ball height is very high to confidently interpret the results, which support both H2 and H3 that are the goals of this study. Finally, limited statistical power because of the modest sample size in the present study (n=15) may have played a role in limiting the significance of some of the statistical comparisons conducted.

Lastly, we want to emphasize that we only show the effectiveness of VR training and performance transfer compared to no training in this study. VR training's effectiveness compared to real training is part of future work by having three groups (no training, real training, and VR training or a mixed training design); therefore, no claims are made regarding VR training's advantages over the real training. Also, because this study focuses on skill transfer from VR to the real world, only a summary of the VR data was presented. We will study the causality of the performance improvement in future work and show a more detailed analysis of ball flight, paddle holding, and posture. We will also present more data from the VR system collected during training representing the motor skill learning process.

7 Conclusion

This paper demonstrates skill acquisition for a skill-based sport in VR and training transfer to the real world. We hypothesized that VR training would improve the participants' performance in ball quality if trained for five VR sessions. Based on this hypothesis, a VR system that simulates ball flight physics in table tennis was implemented and validated by comparing its output with real ball flight using computer vision techniques. A descriptive training system within VR was designed to provide real-time feedback on posture, technique, and ball returns. The system's goal was

to improve the quality of ball returns, evidenced by flatter trajectories and higher speeds. 18 subjects participated in this research and were divided into an experimental group and a control group (we removed 3 subjects from data analysis). The results showed significant improvement for the experimental group after training in VR, while the control group that didn't go through any training saw no significant improvement. The data showed skill transfer from VR to real table tennis. In future works, we plan to compare the effectiveness of VR training with real training. This study offers insight into VR skill acquisition and training transfer by using a system that combines realistic audio-visual stimuli and real-time feedback, supports the validity of VR for training, and provides a low-cost, accessible, time-saving, and effective system for table tennis training in VR.

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