# Touch the Wall: Comparison of Virtual and Augmented Reality with Conventional 2D Screen Eye-Hand Coordination Training Systems

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## Abstract

Previous research on eye-hand coordination training systems has investigated user performance on a wall, 2D touchscreens, and in Virtual Reality (VR). In this paper, we designed an eye-hand coordination reaction test to investigate and compare user performance in three different virtual environments (VEs) – VR, Augmented Reality (AR), and a 2D touchscreen. VR and AR conditions also included two feedback conditions – mid-air and passive haptics. Results showed that compared to AR, participants were significantly faster and made fewer errors both in 2D and VR. However, compared to VR and AR, throughput performance of the participants was significantly higher in the 2D touchscreen condition. No significant differences were found between the two feedback conditions. The results show the importance of assessing precision and accuracy in eye-hand coordination training and suggest that it is currently not advisable to use AR headsets in such systems.

**Index Terms:** Human-centered computing—Human Computer Interaction (HCI); Human-centered computing—Virtual Reality; Human-centered computing—Pointing; Human-centered computing—Touch screens

## 1 Introduction

Among the many applications for virtual reality (VR), training systems to improve the performance of sports athletes have recently attracted attention. One of their advantages is that a particular situation (e.g., a ball with a certain trajectory) can be reproduced as often as needed, which is difficult to do in the real world [14], but a key factor in sports training to enable athletes to master a particular technique. Also, the virtual environment (VE) can be easily tuned to cover diverse training situations depending on the needs of the trainee/trainer and it is easy to collect and analyze a variety of data in such a controllable environment [55]. Moreover, training systems reduce the possibility of the trainee getting injured [33] and a number of skills can be trained effectively at home with them, saving time and money, and increasing productivity.

Previous studies utilized several different VR technologies, such as CAVEs and head-mounted displays (HMDs), [56] as training systems for a variety of sports including, but not limited to: skiing [68], American football [33], basketball [17], and cycling [64]. Although VR technology has some limitations and not all types of training are suitable [55], many agree that VEs can provide great advantages for sports training and that current state-of-the-art technology can be effectively applied to train several different athletic skills [17, 33, 64, 68]. However, in a survey of 227 athletes, Gradl et al. [29] found that just 10.5% had used a VR headset in the past. Nonetheless, 43.1% believed that this technology has potential to improve their performance.

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The eye-hand coordination task, also known as a reaction test, is one of the nine psychometric tasks in the Nike SPARQ system, also called the "Sensory Station" (Nike, Inc., Beaverton, Oregon) – a tool to enhance athletes' perceptual and visual–motor skills [78]. In this task, trainees have to touch a sequence of randomly activated targets as fast and accurately as possible, improving both their reaction time and accuracy. Beyond being implemented on real 2D surfaces (e.g., a wall) [21, 60] or 2D touchscreens [24, 78], this eye-hand coordination task was also explored in VR with and without passive haptic feedback [13].

Current 2D screen-based eye-hand coordination training systems do not change the dimensions of the grid and/or targets and do not record hit positions within a target. Thus, it is not possible to measure throughput and to use precision and accuracy as an assessment criterion. This motivated us to implement a new version of a 2D eye-hand coordination training system that expands the capabilities of previous systems correspondingly. Beyond this, VR and AR systems allow users to interact with mid-air objects, which approaches the challenge of catching a ball in mid-air at different (depth) distances. VR/AR systems are also more affordable and portable compared to a large 2D touchscreen on a sturdy stand.

Previous work [13] implemented an eye-hand coordination test in VR to investigate user performance in terms of reaction time, error rate, and throughput in a Fitts' law task. Participants had to select a sequence of virtual targets with the VR controller or with their dominant hand, either in mid-air or on a real wall (i.e., with passive haptic feedback). The authors found that the mid-air VR controller achieved the best performance, but also that users took longer, made more errors, and had the least throughput with passive haptic feedback compared to when the targets were in mid-air.

Yet, several previous studies [1, 50, 63] reported the opposite outcome, i.e., that haptic feedback results in substantially better user performance. One reason for Batmaz et al.'s [13] results could be the fact that users were not able to see the real wall in the VR HMD, which potentially affected their performance.

AR technology has been used to train climbers in bouldering [19]. However, to the best of our knowledge, there are no studies on using AR HMDs for sports training and specifically none that investigated user performance in the eye-hand coordination task.

In this work, we investigated the following research questions: Can AR and VR headsets be used in eye-hand coordination training systems? How does user performance vary between AR and VR headsets? Does mid-air interaction in VR and AR headsets decrease user performance due to the lack of physical support, which is provided by real world eye-hand coordination training systems?

To answer these questions, we extended Batmaz et al.'s [13] work and designed an eye-hand coordination training system to investigate user performance in three different conditions: VR, AR, and as baseline, a 2D touchscreen. For the VR and AR conditions, participants performed the same experiment both in mid-air and with passive haptic feedback. As in our previous work [13] we use Fitts' law and throughput, which incorporates speed, precision, and accuracy. This approach has the potential to better inform trainers and athletes on how to improve their skills, including how to approach the fundamental speed-accuracy trade-off. Given that VR/AR systems are not only cheaper, but can also be deployed in locations where large touchscreens are not available, our approach gives athletes more opportunities to train, including at home.

## 2 PREVIOUS WORK

### 2.1 Eye-Hand coordination training in sports

In many sports activities, such as volleyball or football, one of the main objectives of traditional training is to improve reaction time. For example, in volleyball, a smash is a technical skills to master, which involves a complex movement that demands good accuracy and putting the ball right on target. There are many factors that affect this skill and some of them are eye-hand coordination, arm swing, accuracy, and timing in hitting the ball [84]. Across many sports, a variety of approaches use eye-hand coordination training systems to train athletes. The effectiveness of these systems is already well-studied. Harpam et al. [32], Poltavski and Biberdorf [59], Wang et al. [78] and Krasich et al. [39] are a few examples of studies that used 2D touchscreens for eye-hand coordination training. In all of these studies, a grid consisting of 8 columns (68.6 cm) and 6 rows (44.5 cm) with equally spaced 48 mm diameter circles were used to assess only the reaction/movement time of the users. Several previous studies have even verified the skill transfer from eye-hand coordination training systems to sports performance [32, 40, 59].

### 2.2 Performance assessment in sports training

Research on user performance assessment with sport training systems suggests that, for efficient assessment of trainees, it is appropriate for trainers to consider essential factors, such as accuracy, precision, and error rate, in addition to time. This extra information enables trainers to provide more precise feedback to trainees, which maximizes the efficiency of training and minimizing the duration of the training period [7, 11, 18, 79]. To distinguish more accurately which factors affect user performance in sport training systems, we can take advantage of the data provided by VR systems, also because they provide a high(er) sample rate [14]. In VR, user performance is influenced by how human perceive the environment [20]. Researchers have shown that human abilities can be improved through different skill training methods, including acuity tests [27], contrast tests [42], and stroboscopic exposure [2]. Previous work also applied these different types of training to athletes and observed that the athlete's performance increased significantly [16, 23].

### 2.3 Fitts' Law

Fitts' law [26] models behavior of the entire human receptor-neural-effector system in pointing tasks. Equation 1 shows the Shannon formulation [51]:

$$Movement\,Time = a + b * \log_2\left(\frac{A}{W} + 1\right) = a + b * ID \qquad (1)$$

In Equation 1, the movement amplitude is A and W is the target size, while a and b are constants, empirically derived via linear regression. The index of difficulty (*ID*) is calculated through the logarithmic term, indicating the task difficulty.

According to ISO 9241-411:2012, throughput is defined as the "rate of information transfer when a user is operating an input device to control a pointer on a display" [35], and we calculated throughput accordingly:

$$Throughput = \left(\frac{ID_e}{Movement\,Time}\right) \qquad (2)$$

In Equation 2, movement time is the time between initiation of the movement and the selection of the target. The effective index of difficulty ($ID_e$) is defined as the "measure of the user precision achieved in accomplishing a task" [35]. We calculated the effective index of difficulty as follows:

$$ID_e = \log_2\left(\frac{A_e}{W_e} + 1\right) \qquad (3)$$

In equation Equation 3, $A_e$ is the effective distance, i.e., the actual movement distance to the target, which incorporates how accurately participants performed the task, and $W_e$ represents the effective target width, which is the distribution of selection coordinates calculated as $W_e = 4.133 * SD_x$, where $SD_x$ is the standard deviation of selection coordinates along the task axis. $SD_x$ is used to measure the precision of the task performance [35, 52, 53].

Beyond precision and accuracy measures, we also measure error rate, which is the rate of correctly selected targets.

Fitts' law, Equation 1, is the most well-known model to analyze a user's pointing performance. In this equation, the user's movement time depends on the target size and distance between targets. As a previous analysis of this relationships shows, target sizes have a significant effect on the average movement time [49]. In this study, we used Fitts law to assess user performance.

### 2.4 Effects of Visual Feedback

Motor learning can benefit from concurrent visual feedback in VR simulators. Advantages of using (real-time) visual feedback have been shown in several studies, e.g., for learning complex motor tasks [54]. Previous research on visual feedback in VR showed that the error percentage decreases through highlighting objects, while increasing selection time and throughput [72]. For example, highlighting targets through changing their color during interaction has significant effects. Besides, user can be provided with other visual cues in the VE, such as shadows [41], motion parallax [69], and texture [34] to obtain a stronger spatial comprehension of the VE, which may also increase selection performance.

### 2.5 Passive Haptic Feedback

Passive haptic feedback in VR involves approaches where the feedback to the user is provided by physical real-world objects that are not under the control of the computer system [48]. While the user is not able to see the peripheral environment due to the VR headset, passive haptics increase the sense of presence in VR and such feedback provides tactile stimulation cues from the environment, which increase user performance while interacting with VEs [37, 62, 76]. Low-cost and low mechanical complexity are the main advantages of passive haptics over active haptics. A study on the effect of using a static surface for passive haptic in VE experiments illustrated that it improves user performance [48].

### 2.6 Effects of Haptic Feedback in VR

Mid-air interaction allows users to interact with a VE without any physical support, and many studies have compared this to haptic feedback in VR [74, 75, 77, 82]. Results showed that the subjects' initial skill level influences which feedback is more suitable for maximizing the learning of discrete time-dependent motor tasks. For targeting tasks Less-skilled subjects benefitted more from haptic guidance, while visual feedback was more advantageous for more skilled subjects. Interestingly, haptic feedback seems to promote learning in a *time-critical* tracking task, while visual feedback decreases performance in this specific context, independent of the task difficulty and subjects' initial skill level [54]. But this result does not hold for other tasks. Still, no previous work has assessed if, in terms of Fitts' law throughput, the combination of haptic and visual feedback is better than visual feedback alone.

## 2.7 Effects of Haptic Feedback in AR

Combining AR and haptic interaction enables users to interact with digital information in the real world through sight and touch. Visuo-haptic augmented reality (VHAR) enhances reality through haptic interaction and enables users to interact more precisely. For this it is important to provide a realistic experience to the AR user, by precisely calibrating all components of the VHAR system (external trackers, cameras, haptic devices) and the spatial relations between them [22].

# 3 Motivation and Hypotheses

Previous research has shown that eye-hand coordination training systems can be used in VR and Fitts' law can be used to assess human performance in VR [13]. However, in our knowledge, there is no previous work that compared eye-hand coordination training systems across VR, AR, and 2D screens.

Current conventional 2D touchscreen-based eye-hand coordination training systems, such as the SPARQ [57], do not change the grid or target dimensions and do not record hit positions within a target. Thus, it is not possible to measure throughput in a meaningful way and use precision and/or accuracy as assessment criteria. This motivated us to develop a new 2D screen eye-hand coordination training system that allows us to change the *ID* of the task, which already expands previous work. Beyond this, VR and AR systems allow users to interact with mid-air objects, including tasks that are similar to the challenge of catching a ball at different depth distances. Since VR/AR eye-hand coordination training systems are well-integrated, it is easy to collect synchronized high-rate data. The systems are also more affordable and portable compared to large 2D screens. This motivated us to compare VR and AR eye-hand coordination training system with a conventional 2D screen.

Based on the review of previous work and current conventional eye-hand coordination training systems, we developed the following hypotheses for our work:

**H1. Users exhibit better performance in conventional 2D eye-hand coordination training systems compared to VR and AR**. Limitations imposed by HMDs, such as the vergence and accommodation conflict [6], presence [65,66], and field of view (FOV) [46] do not affect user performance in real life. Based on this previous work, we expect subjects to perform better with the 2D screen. To our best knowledge, our work is also the first to analyze Fitts' law and the associated (effective) throughput measure for conventional 2D screen eye-hand coordination training systems.

**H2. Similar to VR, AR HMDs can be used for training systems.** Previous studies showed that there is no difference between AR and VR headsets for pointing tasks [8]. Thus, we also do not expect such differences in terms of user performance in this study.

**H3. Passive haptic feedback improves user performance.** Batmaz et al. [13] showed that user performance significantly decreases when subjects hit a surface in VR. On the other hand, user performance increases when a static surface is used in a VR system [15,48]. Here, we changed the interaction method from *hitting* a surface, where the user's palm has to physically interact with the wall, to *touching* it, where only the tip of the user's index finger has to physically interact with the wall, which also improves the accuracy and precision of the targeting movement. Batmaz et al. [13] explained the performance decrease in the VR headset with a lack of agency: since subjects were not able to see their hands in real-life, they did not hit the real surface as hard and fast as they could. By replicating their experiment in AR, we enable users to see their hand, which enables us to investigate this potential explanation.

# 4 User Study

## 4.1 Subjects

We recruited 15 subjects (6 female) from the local university, with an average of 26.6 $\pm$ 3.85 years. All subjects were right handed and they used their dominant hand to execute the task. The headsets were adjusted to match the inter-pupillary distance of each individual. Table 1 shows further information on participant demographics.

Table 1: Participant demographics.

| Daily Mobile Usage (Hours) | Number of subjects | Daily Computer Usage (Hours) | Number of subjects | Watching 3D Movie (times/ Monthly) | Number of subjects | Weekly Mobile Game Playing (Hours) | Number of subjects | Weekly Computer Game Playing (hours) | Number of subjects | Weekly 3D CAD usage (hours) | Number of subjects | Weekly VR Games Playing (hours) | Number of subjects |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0-2 | 3 | 0-2 | 1 | 0-2 | 14 | 0-5 | 14 | 0-5 | 12 | 0-5 | 11 | 0-5 | 15 |
| 2-4 | 5 | 2-4 | 3 | 2-4 | 1 | 5-10 | 1 | 5-10 | 3 | 5-10 | 3 | 5-10 | 0 |
| 4-6 | 4 | 4-6 | 2 | 4-6 | 0 | 10-15 | 0 | 10-15 | 0 | 10-15 | 1 | 10-15 | 0 |
| 6-8 | 2 | 6-8 | 8 | 6-8 | 0 | 15-20 | 0 | 15-20 | 0 | 15-20 | 0 | 15-20 | 0 |
| +10 | 1 | +10 | 1 | +10 | 0 | +20 | 0 | +20 | 0 | +20 | 0 | +20 | 0 |

## 4.2 Apparatus

We used a PC with i7-5890, 16 GB RAM, and RTX2080 graphics, with Unity3D software. For this study we chose two headsets with roughly similar specifications:

*VR headset:* for the VR condition we used an HTC Vive Pro headset (Fig. 1(a)) with a resolution of 2880x1600 pixels and 90 Hz refresh rate. The (diagonal) FOV of the device is 110°.

*AR headset:* For the AR condition we chose a Meta 2 headset (Fig. 1(b)) with 2560x1440 resolution and 60 Hz refresh rate. The FOV of the AR HMD is 90°, larger than most other AR headsets. Since the tracking algorithm of the Meta 2 was not robust enough to track head position while looking at a black flat surface, a HTC Vive tracker was attached to the AR Headset. This tracks the AR HMD with comparable quality as the VR condition. We also added a carton sheet on top of the AR HMD to reduce interference between the tracking devices.

*Hand tracking:* For tracking hand movements, we attached a Leap motion to both VR and AR headsets. For the AR condition, the Leap motion was attached at the front of the AR HMD to both disable and replace Meta's hand tracking hardware. Using external hand tracking also eliminated the potential confound of differences in terms of hand tracking accuracy between AR and VR conditions. Since we showed a virtual hand skeleton in the VR condition to help subjects perceive the position of their hand, we also used the same visualization in the AR condition. This also helped users to understand the position of the virtual cursor at the tip of their index finger. Additionally, we added a small spherical virtual cursor (1 cm diameter) on top of the index finger of the virtual hand to enable the accurate and precise selection of objects in both VR and AR conditions.

*2D Screen:* A 85" 4K LED 120 Hz Samsung TV (Fig. 1(c)) was used for the 2D Screen baseline condition. To detect touch input, a PQ Labs G5 touch frame was attached to the TV.

*Calibration:* For the 2D Screen condition, we tape-measured all displayed target dimensions and distances to confirm that they matched the desired real world sizes.

For the AR and VR conditions, two HTC Vive controllers were attached to the real wall to precisely measure its position and to enable us to replicate it in the VE. Before each participant, we verified the matching. This allowed participants to get precise passive haptic feedback from the wall. We also used the distance between the trackers to match real and virtual world distances.

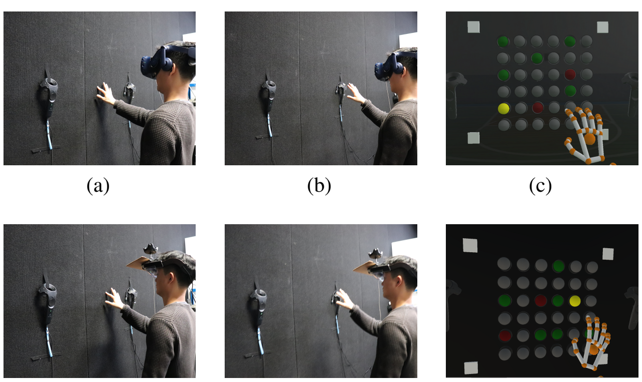
Since we did not use the internal head and hand tracking of the AR HMD, we manually calibrated the display and hand positions of the AR headset. We superimposed virtual and real HTC Vive controllers to adjust the calibration of the AR condition. Subjects were thus able to see their virtual hands over their real ones. Further, we also measured the dimensions of a 28x32x18.5 cm box in the real world and the VE to ensure that distances match in the AR condition at different heights. Before starting each experiment, the experimenter checked that the two real world controllers were superimposed by their virtual representations.


(a) (b) (c)

Figure 1: Study conditions: (a) VR HMD (b) AR HMD and (c) 2D Screen.

### 4.3 Procedure

Before the experiment, we asked participants to fill a demographic questionnaire, after which the experimenter explained the procedure to the participants. Subjects performed the experiment in three different **Environments**: VR, AR, and 2D Screen. Also, for the VR and AR conditions, we used two **Haptic feedback** levels: passive haptic feedback (Fig. 2(a) and Fig. 2(d) respectively) and mid-air (Fig. 2(b) and Fig. 2(e) respectively). A screenshot of the VR scene is shown in Fig. 2(c) and for AR in Fig. 2(f). We replicated the experimental setup and virtual environment used by Batmaz et al. [13]. For passive haptic feedback, we used a wall surface covered with a dense, thick pile of polypropylene (similar to a rug, but dampens sound). While the Leap Motion cannot track the user's hand in contact with normal surfaces, this specific material allowed us to detect hand positions reliably even when the user touched the wall. The standing area for participants was pre-defined, located at the middle of the tracking zone (for both VR and AR), with an offset for the mid-air conditions, or within arm's reach in front of the middle of the screen (for 2D Screen). At the end of the experiment, participants filled a post-questionnaire where they chose their preferred **Environments** and **Haptic feedback** conditions.



(a) (b) (c)

(d) (e) (f)

Figure 2: **Environments** and **Haptic feedback** conditions. First row shows VR (a) passive haptic feedback condition, (b) mid-air condition and (c) scene screenshot. Second row shows AR (d) passive haptic feedback condition, (e) mid-air condition and (f) scene screenshot. Since the Leap Motion covered the camera of the AR HMD, we could not capture a shot of the virtual scene in the AR condition.

The main task in the experiment was to select (push) targets (yellow buttons) in the VE as fast and as accurately as possible with the tip of the dominant hand's index finger. Participants were placed in front of a plane of 6x6 gray spheres with 8 cm spacing. We used three different target sizes $3_{TS}$: small (1.6 cm), medium (3.2 cm), and large (4.8 cm). When the cursor sphere on the participants' fingertip was in contact with the target button, the color changed to blue to provide visual feedback that there was contact with the button. As mentioned above, we used the VR controllers' coordinates to position the virtual wall. When the cursor at the end of the tip of the virtual index finger collided with the virtual wall (or touched the wall in the real world), we detected a "selection" in the passive haptic feedback condition. In the mid-air condition, where we moved the target buttons 20 cm away from the wall, we also moved the virtual wall with them and used the same technique as in the passive haptic feedback condition for selection. The first target sphere was selected randomly among all the spheres. To vary the task and to limit the Fitts' law index of difficulty ($ID$) between 1.94 and 4.39, the next selected target was randomly determined relative to the previous target, chosen among a predefined list of Target Distances $4_{TD}$, 16, 22.6, 24, and 32 cm. After the correct selection of a target, the color of the button turned green, to indicate a successful selection/"hit". If a participant "missed" the target, i.e., hit outside the target, the target button's color changed to red and a beep sound was played. For the conditions that used passive haptic feedback, participants had to push the 3D sphere buttons a specific distance until they touched the wall in front of them and that button turned green. With 2D Screen, participants were told to touch the yellow buttons on the screen. The selection of targets continued until all of the available objects were selected. When there were no other available targets within the set of Target Distances, we finished the trial. We did not allow the algorithm to re-select the same target in a set of trials.

We varied user movement by using 8 different directions: North (N), North West (NW), West (W), South West (SW), South (S), South East (SE), East (E), and North East (NE). For the North, South, East, and West directions, the software randomly selected the second, third, or fourth target in that direction (corresponding to 16, 24, or 32 cm), if that button was still "free" (gray color). For instance, "N3" signifies that next target was going to be three buttons above the current one. For the diagonal directions, we always selected the second target in one of the diagonals, corresponding to 22.6 cm. In total we had 16 factor levels for 8 different directions: North West (NW2), South West (SW2), South East (SE2), North East (NE2), North (N2, N3 and N4), West (W2, W3 and W4), South (S2, S3 and S4), and East (E2, E3 and E4).

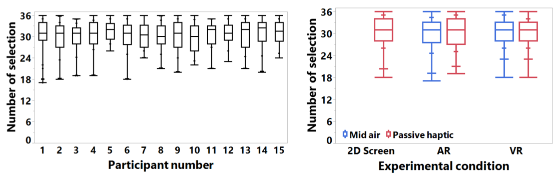
To familiarize the participant with the experiment, they were first given a set of practice trials, until they indicated they were ready for the main study. Also, before the beginning of the experiment, we adjusted the systems to match the height of participants and adjusted the headset and the Leap Motion sensor accordingly.

### 4.4 Experimental Design

In this study, we used a two-factor design with two **Environments** ($2_{VE}$ = VR and AR) conditions with two **Haptic feedback** conditions ($2_F$ = passive haptic and mid-air), comprising $2_{VE} \times 2_F = 4$ conditions. We additionally used another environment, a 2D Screen condition, as baseline. These $(2 \times 2 + 1 =)$ 5 conditions were counterbalanced across our 15 subjects using a Latin square design. To vary the $ID$, we varied target sizes, as mentioned in the procedure section, using three levels for each combination. Based on the different values for $4_{TD}$ (which varied within the trial set) and $3_{TS}$, we evaluated 10 unique $ID$s between 1.94 and 4.39. We measured time (seconds), error rate (%), and effective throughput (bits/s) of the subjects for data analysis. Since we terminated a set of trials when there were no more targets that fulfilled the $ID$ restriction, we did not collect a fixed number of data points in every set. In each set of trials, we collected approximately 29-30 data points (average 29.48) for a total average of 1275 data points per subject. In total, we collected 19133 data points. Each main experimental condition took about 8-10 minutes and subjects were instructed to rest at least 5 minutes between conditions while an experimenter verified the calibration of the next condition in the system.

# 5 RESULTS

Before data analysis, we explored the data and verified that we had collected (approximately) the same amount of data points for each experimental condition from each subject. Below, we show the average of collected data from each subject and condition as quantile box-plots in Fig. 3(a) and Fig. 3(b), respectively.




(a) (b)

Figure 3: Quantile box-plots showing minimum, 2.5%, 10%, 25%, median, 75%, 90%, 97.5% and maximum for average number of target selection for each (a) participant and (b) experimental condition.

We analyzed the results using repeated measures (RM) ANOVA with $\alpha = 0.05$ in SPSS 24. We deleted "double click" data (0.96%), where the next target was selected without hitting another button. The data was not normal, even after log-normal transformation, so we used ART [83] before RM ANOVA for each dependent variable, as ART enables us to examine interaction effects between factors, which standard non-parametric tests cannot. We used the Sidak method for post-hoc analyses. In figures, *** is used for $p < 0.001$, ** for $p < 0.01$, and * for $p < 0.05$.

## 5.1 Experimental Conditions Results

In first part of our analysis, we analyzed the data across all five experimental conditions, 2D screen, VR passive haptic feedback, AR passive haptic feedback, VR mid-air, and AR mid-air conditions for time, error rate and throughput. These results are shown in Table 2 and Fig. 4.

Table 2: 2D, VR, and AR passive haptic and mid-air comparison

| | Experimental Conditions | ID | Experimental Conditions x ID |
|---|---|---|---|
| Time | F(4, 56)=54.35 p<0.001 | F(9, 126)= 92.28 p<0.001 | F(36,504) =8.32 p<0.001 |
| Error rate | F(4, 56)=15.59 p<0.001 | F(9, 126)= 76.9 p<0.001 | F(36,504) = 2.775 p<0.001 |
| Throughput | F(4, 56)=126.56 p<0.001 | F(9, 126)=12.50 p<0.001 | F(36,504) = 5.20 p<0.001 |

The result of the post-hoc tests fairly clearly identify 3 different groups: 2D-screen, both AR conditions, and both VR conditions. Given this grouping, we proceeded to analyzed subsets of the results for **Environments** and **Haptic feedback** in more detail.

## 5.2 Detailed Analysis Results for Environments

First, we analyzed only the passive haptic feedback data for the VR and AR conditions and the 2D Screen to the compare user performance across various environments for eye-hand coordination training. Results are shown in Table 3 and Fig. 5.

### 5.2.1 Time results

The results for the time dependent variable are shown in Table 3 and Fig. 5(a). Subjects were slower with the AR condition compared

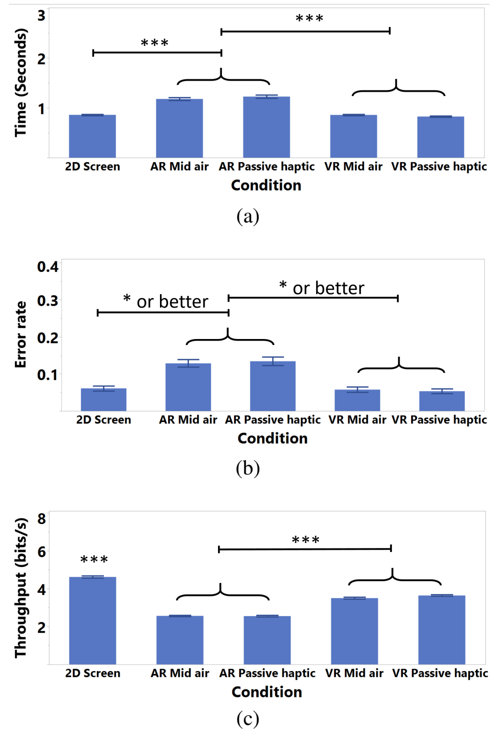



Figure 4: Analysis across all five experimental conditions for (a) time, (b) error rate, and (c) throughput.

Table 3: 2D, VR, and AR passive haptic comparison

| | Environments | ID | ID x Environments |
|---|---|---|---|
| Time | F(2,28)=49.59 p<0.001 | F(9,126)=65.075 p<0.001 | F(18, 252)=8.359 p<0.001 |
| Error rate | F(2,28)=17.25 p<0.001 | F(9,126)=61.40 p<0.001 | F(18,252)=4.70 p<0.001 |
| Throughput | F(2,28)=141.08 p<0.001 | F(9,126)=8.69 p<0.001 | F(18,252)=5.46 p<0.001 |

to VR and 2D Screen. For time, there was no significant difference between VR and 2D Screen conditions.

### 5.2.2 Error rate results

The results for the error rate dependent variable are shown in Table 3 and Fig. 5(b). The error rate was higher in AR compared to VR and 2D Screen conditions. There was no significant difference between VR and 2D Screen conditions for error rate.

### 5.2.3 Throughput results

The results for the throughput dependent variable are shown in Table 3 and Fig. 5(c). Throughput performance of the subjects was significantly higher in the 2D Screen condition, compared to VR and AR. Moreover, subjects throughput was lowest in the AR condition.

## 5.3 Detailed Analysis Results for Haptic Feedback

In this third part of our analysis, we compared only the VR and AR conditions to analyze the difference between passive haptic feedback and mid-air interaction in detail. The results are shown in Table 4.

**Haptic feedback** was not significant (N.S.) for the time, error rate, and throughput dependent variables. Moreover, two-way RM ANOVA results confirmed that there was no significant interaction between **Environments** and **Haptic feedback** conditions for time (F(1,14) = 1.554, N.S.), error rate (F(1,14) = 1.061, N.S.) and throughput (F(1,14) = 1.157, N.S.).

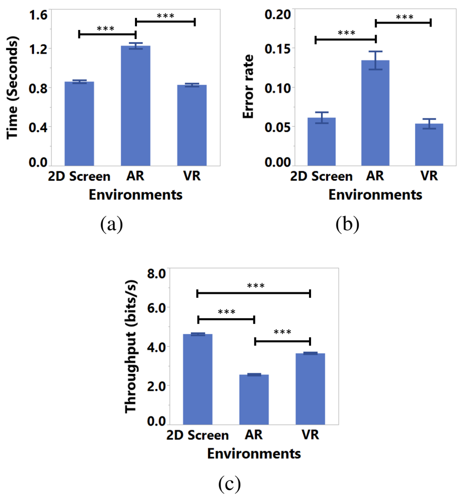



Figure 5: **Environments** condition analysis for (a) time, (b) error rate, and (c) throughput.

Table 4: Feedback results for VR and AR

| | Environments | Feedback | ID |
|---|---|---|---|
| Time | F(1,14)=113.46 p<0.001 | F(1,14)=0.009 NS | F(9,126)= 74.76 p<0.001 |
| Error rate | F(1,14)=29.24 p<0.001 | F(1,14)=0.89 NS | F(9,126)=50.36 p<0.001 |
| Throughput | F(1,14)=163.79 p<0.001 | F(1,14)=0.94 NS | F(9,126)=7.12 p<0.001 |

### 5.4 Task repetition

We also analyzed the performance improvement of participants across repetitions. At the beginning of the experiment, we informed subjects that we are collecting data for sports training applications and asked subjects to select targets as fast and as accurately as possible. We did not give users performance feedback during the experiment.

As Fig. 6 shows, subjects were getting faster (Fig. 6(a)), made fewer errors (Fig. 6(b)), and their throughput increased with each repetition (Fig. 6(c)) in the VR condition. However, while subjects' error rate increased with each repetition in AR, their throughput and time did not change.

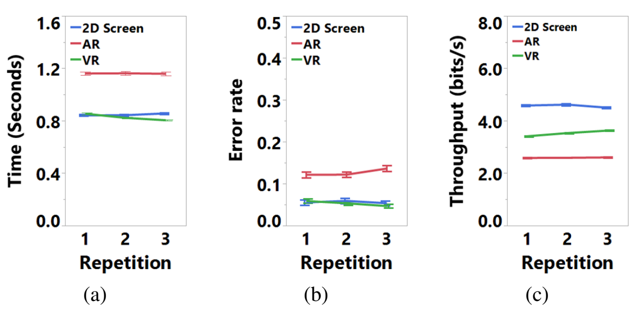



Figure 6: Task repetition results for (a) time, (b) error rate, and (c) throughput.

### 5.5 Movement Analysis

To simplify the presentation of the results, we analysed the data for movement direction, i.e., into which direction participants moved their hand, and movement distance, i.e., the distance between two targets, separately. In one-way RM ANOVA results for movement direction and distance, we found that all dependent variables had a normal distribution. Only for movement direction, error rate ($\chi^2(27) = 54.99, p<0.01, \varepsilon = 0.638$) and throughput ($\chi^2(27) = 41.87, p<0.05, \varepsilon = 0.584$) both violated sphericity. For these two dependent variables analyses, we used Huynh-Feldt correction since $\varepsilon < 0.75$. The results are shown in Table 5 and Fig. 7.

According to these results, subjects were slower and made more errors with targets that involved longer distances, i.e., 32 cm (Fig. 7(b), Fig. 7(d)), and for movements in the upward direction, i.e., North (Fig. 7(a), Fig. 7(c)). Moreover, subjects throughput decreased significantly when the movement involved only short distances, i.e., 16 cm (Fig. 7(f)). Since effective throughput is calculated as $ID_e$ divided by movement time, this shows that subjects effectively performed a task with higher difficulty. Based on the $ID_e$, Equation 3, our results in Fig. 7(e) and Fig. 7(f) show that movements N2, S2, E2, and W2 are representative of larger selection distances and better accuracy (due to lower SDs).

Table 5: Movement Analysis

| | Movement Direction | Movement Distance |
|---|---|---|
| Time | F(3, 42)=117.66 p<0.001 | F(7, 98)= 9.52 p<0.01 |
| Error rate | F(3, 42)=4.085 p<0.05 | F(4.47, 62.55)= 4.09 p<0.01 |
| Throughput | F(3, 42)=212.62 p<0.001 | F(5.98, 83.743)=16.186 p<0.001 |

### 5.6 Subjective results

To evaluate user perceptions of the different conditions, we applied a 7-point Likert scale in our survey. 8 subjects preferred the VR condition, 7 preferred 2D screen and none preferred AR. In the interviews after the experiment, most of the reasons given for preferring VR and 2D screens over the AR environment were due to the fact that subjects felt it was easier to use these systems (3 participants for VR and 2 for 2D Screen), they felt they were more accurate (2 participants for VR), they were more in control of their movements (2 participants for 2D Screen), and 2D screens seemed to be the more realistic solutions to them since they did not have to wear a headset (3 participants). 3 participants chose VR over 2D screen, because it was more similar to how they interact in the real world, i.e., the motions included interaction in depth. 2 participants chose the 2D screen over VR, because it afforded a larger FOV. In our AR/VR experiment conditions, 9 participants preferred to select the target with passive haptic feedback and the remaining 6 preferred mid-air interaction. Reasons behind preferring touching the wall given were "less tiring" (3 participants), having an increased "sense of reality" (3 participants) or "agency" (1 participant), "better perception of depth" (1 participant) or "easier interaction" (1 participant). For those who preferred mid-air interaction the reasons were being "fast and flexible" (3 participants) or "less tiring" (3 participants).

None of the participants found it very easy to interact with the virtual targets in the AR passive haptic interaction mode (1-very easy, 7-very difficult, the median result was 4-neutral), and none of them found it very easy or easy to interact with virtual objects in the AR mid-air interaction mode (median: 5-somewhat difficult). 8 out of 15 participants expressed that it was easy to select targets in the VR passive haptic condition, (the median result was 3-somewhat easy). Besides, in the VR mid-air interaction condition with virtual targets, 9 participants thought it was easy (the median result was 3). 7 participants found it very easy to interact with the target grid in 2D Screen (the median result was 2-easy). In comparison with

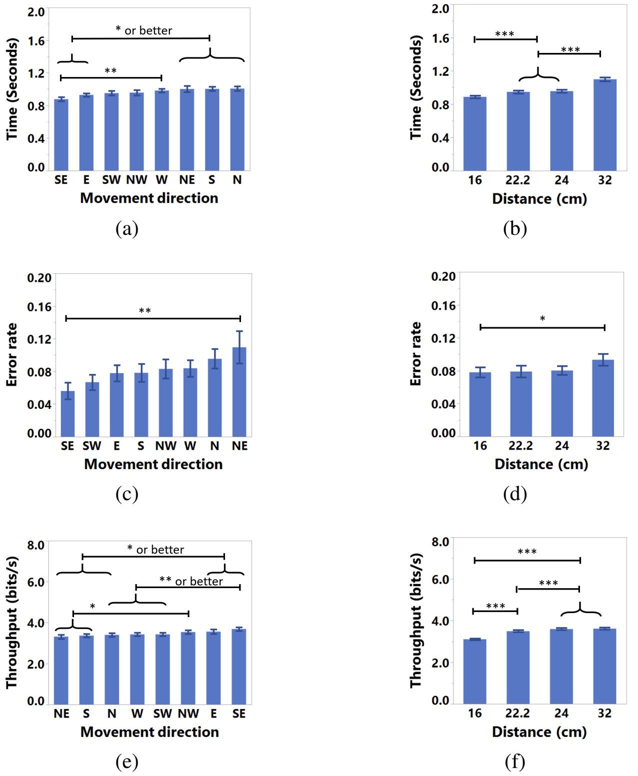


Figure 7: Time analysis for (a) movement direction and (b) movement distance. Error rate analysis for (c) movement direction and (d) movement distance.Throughput analysis for (e) movement direction and (f) movement distance.

mid-air selection, 5 participants thought using the wall did not have any effect on their selection time. Half of the participants (7 out of 15) expressed feeling slight fatigued after the experience (1- I feel rested, 7- I feel extremely fatigue, median: 5).

### 5.7 Fitts' Law Analysis

Since the number of target directions and distances were randomly selected, we first show the histogram of collected data points across IDs in Fig. 8(a). According to these results, we collected more than 1000 data points for each ID. For ID=2.58, we collected the most (3779) and for ID=4.39 the least (1082). For Fitts' law analysis, we averaged these data points for each ID.

Fitts' law linear regression results were MT = 0.37 + 0.154 * ID, $R^2 = 0.91$ for the 2D Screen, MT = 0.39 + 0.136 * ID, $R^2 = 0.9$ for VR and MT = 0.24 + 0.308 * ID, $R^2 = 0.96$ for the AR condition. These results are shown in Fig. 8(b).

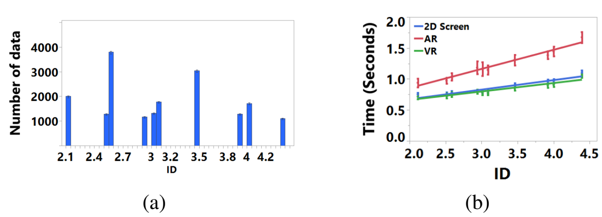


Figure 8: (a) Histogram of collected data points for each ID, (b) Fitts' Law results for Environments.

## 6 Discussion

In this work, we studied eye-hand coordination training systems in VR and AR and compared them with the conventional approach, which uses 2D touchscreens.

Results showed that there is no significant difference between 2D Screen and VR conditions in terms of time and error rate. However, throughput results were significantly higher for 2D Screen than VR, as expected by **H1**. These results also match previous results comparing real-world and virtual world interaction [6, 7]. The effect of different depth cues or stereo deficiencies, such as the vergence-accommodation conflict, are some of the potential explanations for this difference. Our result also confirms that there is (still) a difference between real-world 2D screen systems and VR and AR application, however our results reveal that especially VR systems have strong potential for eye-hand coordination training systems.

The throughput result for different **Environments** also shows the importance of accuracy, precision, and throughput assessment; without looking at the throughput, i.e., looking only at time, error rate, and subjective preferences, one could come to the conclusion that there is no difference between 2D screens and the VR conditions for eye-hand coordination training systems. However, the previous literature, such as [6, 7, 36, 45, 71], showed that user performance is different in VR. As the previous literature suggests that precision and accuracy play a key role in user performance assessment [9, 10, 12], throughput – which takes time, precision, and accuracy into account – should be applied within training systems and simulators.

In the AR condition, subjects were slower, made more errors, and their throughput decreased compared to the VR and 2D Screen conditions. We further investigated this user performance decrease for each subject and individual condition, but could not find any definite explanation for the decline in performance. Moreover, none of the subjects preferred the AR condition to VR or 2D Screen. Yet, the results of the Fitts' law analysis confirm that Fitts' law can be used to assess user performance more accurately in AR eye-hand coordination training systems. Thus, our hypothesis **H2** is supported. Nevertheless, practitioners have to consider the performance difference between these conditions.

By eliminating differences in head and hand tracking quality through external systems, VR and AR systems were roughly similar. The chosen AR and VR headsets had approximately the same specifications. Thus, we believe that the difference between AR and VR conditions was caused by the drawbacks and limitations of current AR headsets. For example, a 60 Hz refresh rate might not be good enough to render fast hand movements in AR.

Another issue that might have affected user performance could be the sheer number of devices involved in the AR condition - Meta 2, HTC Vive tracker, and the Leap motion. Although we built our setup to keep the differences between the AR and VR conditions to a minimum, any issues with the combination of these systems could affect the user performance. For the hand-based interaction condition we only added a Leap Motion, which is today a fairly standard add-on for VR/AR systems. We acknowledge that using a different software/hardware platform could cause performance differences. E.g., the AR system's native tracking was not stable enough for a reasonable Fitts' law study and to enable a fair comparison (one of the goals of our work). Even though subjects did not complain about the weight of the tracker, it could have decreased the subject's comfort, which could reduce presence and affect user performance. For broad deployment some engineering effort would be needed to improve on this.

A third potential explanation for the difference of the AR and VR conditions could be the rendering of the virtual objects in the real world. We showed a virtual hand skeleton to increase the perception of the user's hand position. As mentioned in the study description, we chose to show virtual hands to help users perceive the position of their hand in space. This also helped subjects to understand the position of the cursor at the tip of their index finger. Subjects might also have expected to be immersed either completely in VR or in reality. The composite of both options might have created minor visual distractions due to slight mis-registration, which might have decreased their performance as they needed to align the virtual targets and their real hand. Or the integration with the external tracking system was inferior to the tracking in the VR condition. This might have created slight delays in AR, which might have confused participants when watching their hand closely.

Another explanation of the results could be perceptual-cognitive issues [44]. For example, Swan et al. showed that users can overestimate distances in AR [70]. Even though we carefully matched real and virtual world distances in AR and VR, any distance perception issues in the AR condition might have affected user performance.

In the second part of the data analysis, we compared user performance with and without passive haptic feedback. Our results on **Haptic feedback** showed that using a hard surface for passive haptic feedback does not affect user performance. In further analysis, we also did not find any significant interaction between **Environments** and **Haptic feedback**, which suggests that being able to see their hand in the real world does neither increase nor decrease user performance. One potential reason that our results does not match previous work by Batmaz et al. [13] is that the interaction style we used in this study was different. While Batmaz et al.'s work showed that passive haptic feedback significantly decreases user performance when they "hit" the wall with their palms, in this study participants "touched" the wall with the tip of their index finger, which seems to have reduced the user performance difference between the passive haptic feedback and the mid-air condition. However, as suggested by previous literature, e.g., [15], passive haptic feedback did not increase user performance compared to the mid-air condition. Thus, we can partially accept our hypothesis **H3**.

We also highlight that interaction style significantly affects user performance and thus should be considered as an independent variable in sports training systems. For instance, while the BATAK system [60] requires "hitting" objects, the Nike SPARQ system [57] requires "touching" objects on a 2D screen. None of these systems record how accurately the athlete hit the targets. As our study measures accuracy and precision (as well as throughput), our results present a significant improvement over such systems.

We also explored performance measurements with Fitts' law in mid-air VR and AR eye-hand coordination training systems. Before applying VR and AR systems for real world training applications, the usability of these systems had to be validated with quantitative results and compared to the previous literature on Fitts' Law. Thus, as in previous studies, we recruited our subjects from the local university, none of whom had an interest or professional experience in sports. While our questionnaire included only an option for "0-5 hours", we found that most of our participants, 12 out of 15, do not play 3D VR games weekly, which means that the frequency of VR/3D game usage was low. Also, previous work showed that user performance changes with expertise level [55]. Thus, we believe that the results of our study might vary with different expertise levels, but can also state that our results are directly applicable to novice athletes. The literature on skill transfer between VR simulators and the real world is unfortunately still inconclusive for sports training [30, 55, 85]. Thus, there is a need to first understand the properties of 3D VR training systems, before fully investigating them with athletes. As mentioned in the motivation section, VR and AR systems allow users to interact with objects in mid-air, which can be used to simulate important parts of sports tasks, such as catching a ball at different depth distances. Also, users can easily repeat various scenarios in their training. Hence, VR and AR systems have strong potential for sports training systems. We also believe that before using VR or AR training systems on athletes, we need to explore the used systems further to identify the effect of technical differences and the overall effect of these systems on human performance. The results of our throughput analysis and the difference between 2D Screen and VR conditions also supports this argument. Similarly, the detailed investigation of passive haptic feedback in VR and AR helped us to identify the effect of crucial feedback mechanisms for eye-hand coordination training systems. Our work does not focus on a specific sport nor user performance variation across different sports.

As expected, we observed a performance increase over time during the experiment, which matches previous work on Fitts' law [3, 28, 38, 61]. Yet, the number of trials in our work was not large enough to analyze long-term learning. Subjects repeated each specific set of tasks (only) three times, which was still sufficient to analyze participants' performance in terms of Fitts' law.

Previous studies on Fitts' law and human motor performance have already investigated the effects of movement direction on user performance, including [5, 7, 12, 25, 31, 43, 47, 67]. The results of our study match the outcomes of this previous literature; subjects are slower when they move their hand upwards. Also, their movement time increases and their accuracy decreases when they reach for further away targets [26, 58, 73, 80, 81]. Hence, we did not analyze movement direction further in this work.

According to the subjective results, subjects did not report significant physical or mental fatigue after the experiment. We also did not observe any task fatigue, which is also supported by the 7-point Likert scale results. We decreased potential task fatigue by adjusting the height of the target platform according to the height of each participant and by allowing users to freely position themselves in front of the wall and 2D Screen. Further, subjects did not report any simulator or motion sickness which could have affected their performance, likely since the participants did not move in the VE and they did not have to move their heads in the virtual and physical space much, nor did we observe corresponding symptoms during the experiment in our participants.

## 7 Conclusion and Future Work

In this study, we investigated eye-hand coordination training system using a Fitts' task in VR and AR conditions and compared them with a 2D screen-based system. We used an approach based on throughput measurements, which incorporates speed, precision, and accuracy. This approach can better inform trainers and athletes on how to improve their skills, including how to approach the fundamental speed-accuracy trade-off. We also investigated passive haptic feedback and mid-air interaction, in both VR and AR conditions. Results showed that an AR headset significantly decreases user performance and passive haptic feedback does not improve user performance. Since VR and AR systems are more affordable and easier to deploy in many locations, including at home, such systems have great potential as sports training systems. The results of our work can be used to inform VR and AR research, as well as lead to new sports training systems to improve the performance of athletes.

In the future, we plan to collect data from professional athletes who have experienced real world training and look at the corresponding learning effects in VR and AR systems. We also want to investigate skill transfer from VR/AR systems to real-world performance. Eye-hand coordination training systems could also be used in rehabilitation and medical research [4] and we plan to expand our work to explore this potential avenue of applications for eye-hand coordination training in VR and AR.

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