On the Effectiveness of Virtual Eye-Hand Coordination Training with Head Mounted Displays

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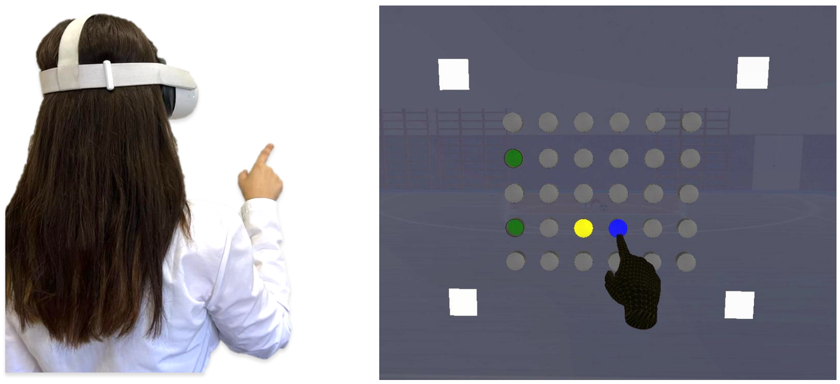

(a) (b)

Figure 1: Eye-Hand Coordination Training system(a) used with a virtual reality head mounted display. (b) the virtual scene, as seen by the participant.

Abstract

Eye-hand coordination training systems are used to train participants' motor skills and visual perception. Such systems have already been tested in Virtual Reality, and the results revealed that Head Mounted Display-based systems have the potential to improve the motor training. However, this was only investigated in an hour-long study. In the longitudinal study reported here, we analyzed the motor performance of three participants in ten sessions with three different assessment criteria, where participants were instructed to focus on speed, error rate, or complete the training freely (with no instructions). We also assessed the effective throughput performance of the participants. Our results indicate that effective throughput can be potentially used as an additional assessment criterion. We hope that our results will help practitioners and developers design efficient Virtual Reality training systems.

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

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1 Introduction

Virtual Reality (VR) systems have become much more affordable and thus accessible in recent decades. Virtual reality environments or virtual scenes are most commonly visualized through head-mounted displays (HMDs), and besides many other applications, they could be used as training systems [60].

HMD-based VR training systems offer many advantages over conventional methods. Firstly, VR systems allow trainees to be exposed to exactly the same scenario several times or can apply a limited amount of randomization to create controlled irregularities in the task [29, 43]. Secondly, HMDs provide a safer environment for novice trainees when faced with potentially dangerous tasks (e.g., fire-fighter training [20]). Further, using VR systems has been shown to reduce the number of accidents and injuries compared to real-world training systems. For example, Huang et al. showed that HMD-based VR systems significantly decrease the number of hits received by an athlete during training [27]. Thirdly, a large amount of data can be collected more easily in such digital systems, compared to conventional analog systems with the associated custom hardware [13]. Finally, trainees can experience asynchronous training wherever they want, whenever they want, without needing the presence of a trainer. In addition, HMD-based VR systems offer great promise for training and education applications, where trainees can learn or improve certain skills on their own without needing other physical training equipment [41]. This increases accessibility and inclusivity for the trainees.

Sports are a frequent target for HMD-based VR training systems, and various studies investigated the impact of such systems on user performance in sports-based training applications [1, 26, 31, 34]. One of the critical skills to train in sports is eye-hand coordination (or the peripheral eye-hand response). For instance, Burris et al. showed that higher sensorimotor abilities contribute to the performance of professional baseball players [16]. Systems designed for eye-hand coordination training (EHCT) aim to improve sensorimotor skills and perceptual performance. Such systems are referred to as *Eye-Hand Coordination Training Systems* (EHCTSs) from here on.

EHCTSs include a visual feedback mechanism for stimuli, and the trainee is asked to "hit" a random sequence of these stimuli. EHCTSs are also known as *reaction-training systems* since they are also used to decrease the reaction time of the trainee when hitting the stimuli. Such training systems have been implemented for 2D touchscreens [58], tablets [21], and 2D real-world surfaces [19]. 2D screen versions of EHCTSs are used in various sports to improve trainee performance, such as hockey [49] and football [25]. Furthermore, EHCTSs are also sold commercially, e.g., by Nike [45] and Batak [50]. Considering the positive impact of VR-based training systems in various sports, including basketball [17], American football [27], skiing [54], cycling [52], and other fields such as e-sports [44] and rehabilitation [23], the potential of EHCTSs becomes even greater if they were implemented using HMD-based VR systems.

The previous literature on EHCT showed that HMD-based VR systems can be used as an alternative to conventional EHCTSs [9,11]. These studies consist of user experiment that took place in one session. Therefore, the impact of longitudinal training sessions on trainee motor performance skills is still unknown. Further, studies on HMD-based VR training systems mostly required the trainees to focus on the efficiency and efficacy of the approach in general [18, 42,46,55]. So, these studies did not analyze the impact of different task execution strategies (e.g., completing the tasks fastest, the most accurate, the most precise, etc.) during sensorimotor learning in a longitudinal user study of HMD-based VR EHCTS.

To fill this gap in the literature, we replicated an HMD-based VR EHCTS environment from previous work [12] and conducted a longitudinal user study to understand the efficiency of this EHCTS with three different task execution strategies. To assess the change in motor performance across sessions, we asked participants to either focus on lowering their task execution time, which we refer to as a **speed-focus** strategy, to focus on selecting targets as closely as possible to the target center, which we refer to as **accuracy-focus**, or to simply complete the task without a particular focus, which we refer to as **no-focus**.

We hypothesize that (**H1**) different task execution strategies have a different impact on long-term user performance for HMD-based VR EHCTSs, and (**H2**) it is possible to use effective throughput as a long-term assessment criterion for HMD-based VR EHCTSs. Overall, our contributions are:

- *A comparison of speed-focus, accuracy-focus, and no-focus training approaches within a longitudinal study,*
- *Using effective throughput as an assessment criterion in a longitudinal VR EHCTS study, and*
- *Suggestions for analyzing performance and reporting feedback to the trainees in VR EHCTS.*

Here, we report our results from a preliminary user study conducted with three participants, where each participant was assigned one training strategy over the course of 12 days. Our results show that training strategy plays an important role in psychomotor improvement, and throughput can be used as an assessment criterion to observe the motor performance progress of the participants. We hope that our findings can guide practitioners, developers, and trainers to design more efficient HMD-based VR EHCTSs in the future.

2 Previous Work

2.1 Eye-Hand Coordination Training

EHCT uses psychometric tasks that aim to both decrease the reaction time of the trainee and increase perceptual performance. EHCT requires trainees to detect a certain stimulus and react to it with their hands, which can be extended to many activities in daily life. Even though it applies to a variety of application scenarios, EHCTS are most frequently used for training in various sports, e.g., [17,27], and other fields such as e-sports [44], military aircraft pilot training [14], and rehabilitation [23]. In 2D touchscreen and other hardware-based EHCTSs, a target randomly appears on a surface, and the trainees are instructed to select the target as swiftly and smoothly as possible. Previous studies investigated the skill transfer and the effectiveness of such EHCTSs, as well as the effect of daily human variations, such as sleepiness [58]. Overall, previous work showed that EHCT helps trainees to react faster to visual stimuli, which also increases trainee performance in sports, directly affecting game results [25].

Eye-hand coordination of the trainees can be improved through activities involving physical systems, e.g., through ball drops, juggling, or wall-ball. However, many trainers prefer digital systems since they can collect data about the objective motor performance of the trainee and provide direct feedback based on it. This approach also allows the trainee and trainer to adjust the learning strategy and decrease the time required for the trainer. Previous commercial EHCTSs relied on 2D touchscreens (e.g., NIKE's system [45] or Meyend [40]) or mounted buttons with lights on a frame (e.g., BATAK [50]).

2.2 Eye-Hand Coordination Training in VR systems

The recent advances in VR technology enable HMDs to be used for EHCT [11]. HMD-based VR systems are particularly useful for the direct collection of 3D movement data, since eye-hand coordination tasks require actions to be performed in 3D space. VR-based EHCTSs can thus help trainers to provide feedback to the trainees based on this collected data.

A VR-based EHCTS presented in previous work [11] used a task similar to the Nike SPARQ sensory station [45]. In these setups, there is a layout of potential targets in a virtual setting, but only a single target gets highlighted at a time. Participants see a virtual cursor representing their fingertip in real-time and select each highlighted target in turn as fast and precisely as possible with that cursor. The authors showed that HMD-based VR EHCTSs have the potential to improve visual-motor skills. In follow-up work, Batmaz et al. [9] conducted another user study and compared user performance across VR, AR, and touchscreen-based systems. The results showed that user performance in HMD-based VR system was at the same level as in touchscreen-based systems in terms of time and error rate [9]. However, user performance was significantly worse in the HMD-based AR training system. Further analysis also revealed that trainees performed the best with HMD-based VR EHCT while interacting with objects in mid-air, with their dominant hand, and with a vertical task plane orientation. In another study, the authors also analyzed the effect of different target and cursor sizes [12]. The results showed that user performance increases when the target size increases, but not when the size of the cursor attached to the user's hand changes.

Mutasim et al. [30] analyzed the gaze movements of participants while they executed HMD-based VR EHCT. The authors identified that with current HMDs, most users have to flex their necks substantially to see all the targets in the 6x6 design used in previous work [9,11]. They also showed that EHCTSs should be designed to reduce the visual search time for the next target. As a result, they proposed to use a 5x6 target design instead of a 6x6 design, which ultimately allows users to see all targets in their field of view at once while being able to reach all of them directly.

The aforementioned studies helped us understand how human performance and decision making is affected by HMD-based VR technologies [35]. Still, the literature lacks a longitudinal study that analyzes the long-term impact of HMD-based VR EHCTSs for training. In this study, we used the above-mentioned 5x6 target layout in a 12-day longitudinal experiment to investigate the long-term effects of HMD-based VR EHCTSs on motor learning.

2.3 Motor Performance Assessment Criteria

An important research question for training systems is how to assess the performance of the trainee and how to provide effective feedback to them [51]. While some work proposed training systems without analyzing the efficiency of the learning strategies [42, 46], others only assessed user performance through execution time [57]. Yet, participants might use different task execution strategies, which might then affect the outcome of the training.

A recent study proposed using precision as the primary assessment criterion [6]. The results showed that participants can learn how to execute the task and perceive the stimuli faster if they are motivated to prioritize precision over performing the task quicker or to focus on the feedback. The authors claim that a precision-focused strategy would help users to speed up their sensorimotor learning and rapidly adapt to the task [7].

2.4 Fitts' Law and Effective Throughput

Fitts' law models the time required for a human to perform a task as a function of the target size and the distance [22]. While there are multiple approaches, one of the most widely used ones in human-computer interaction research is MacKenzie's Shannon formula (Equation 1) [36], which is based on information theory:

$$MovementTime\,(MT) = a + b * \log_2\left(\frac{A}{W} + 1\right) = a + b * ID \quad (1)$$

where A and W represent the target distance and the target size, respectively. The log term represents the task difficulty and can be described as the *index of difficulty*, ID. The coefficients a and b are empirically derived via linear regression.

Fitts also defined a second formula to analyze user performance, called the index of performance. After decades of research, one of the most well-known versions for the index of performance was proposed by MacKenzie [36], motivated by the Shannon capacity theorem, and now known as throughput based on effective measures (or effective throughput for short).

$$Throughput = \left(\frac{ID_e}{MovementTime}\right) \quad (2)$$

In Equation 2, movement time represents the task execution time and ID_e describes the effective index of difficulty, with accounts for the effect of the combination of user's *accuracy and precision* in ISO pointing tasks [28] as in Equation 3:

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

where the effective target width W_e is calculated as $W_e = 4.133 \times SD_x$ with SD_x being the standard deviation of the distance between the target center and the selection coordinates projected onto each task axis. According to previous work [28, 37, 38], SD_x represents the accuracy of the task execution. The effective target distance A_e in Equation 3 is calculated as the average real distance traversed until the selection, with a bi-variate formulation.

Fitts' Law and effective throughput are presented in the ISO standard as an "assessment approach for the design of physical input devices for interactive systems" [28]. The task precision or "measure of the user precision achieved in accomplishing a task" [28] is represented as ID_e in ISO 9241-411. The (relative) proximity of the selected points is referred to as precision in this context. In our work, we use the ISO 9241:411 equations to analyze the accuracy (SD_x) and precision (ID_e) of the participants.

2.5 Effective Throughput as Assessment Criterion

Effective throughput has been proposed as an assessment criterion for VR systems by Teather and Stuerzlinger [56]. It is particularly advantageous since it combines task execution time, accuracy (SD_x, see [37]), and precision (ID_e, see [28]) into one measure as shown above in 2. This single measure allows a trainer to get a general overview of the trainee's progress at a glance. Previous studies on HMD-based VR EHCTSs also suggested using effective throughput as a performance assessment criterion [9, 11, 12]. Looking at the effective throughput helped researchers identify that participants' precision decreases in HMD-based VR EHCTSs compared to conventional ones, which might be related to the conflicting depth cues in current stereo display technologies [2, 3, 5].

MacKenzie and Isokoski also proposed that effective throughput is speed-accuracy invariant, e.g., the throughput performance of the participants does not vary even if they focus on speed or accuracy during task execution [37]. However, previous work revealed that effective throughput can change with task execution strategy. This was first analyzed by Guiard et al. on 2D screens and then Olafsdottir et al. [47], which asked participants to execute a Fitts' law task with different execution strategies. The results showed that user performance varies across execution strategies. Recent work also investigated effective throughput (in)variance for 3D mid-air interaction [10]. The results demonstrated that throughput is dependent on task execution strategy, i.e., it is *not* invariant.

To our knowledge, previous studies limited the analysis of effective throughput across, at most, a few sessions. For example, Boritz and Booth analyzed the effective throughput for four sessions [15]. Thus, we do not know how throughput would change after much longer training. In our current work, we thus analyze how the effective throughput performance of participants evolves with each session across a longer time span.

In our current study, we do not aim to investigate the effective throughput (in)variance for Fitts' law task. Yet, as in previous EHCT work [9], we still use effective throughput as an assessment criterion to understand the motor-skill evolution of the participants in a longitudinal HMD-based VR EHCT study.

3 User Study

To test our hypotheses, we designed an experimental setup for EHCTS with a HMD-based VR system. The used virtual scene was similar to previous works [12, 30].

3.1 Participants

We recruited 3 participants (2 female, 1 male) aged between 19 and 23 years (mean = 21, SD = 2). Participation was voluntary, and no incentives were provided for taking part in this study. All participants were students from the local university. 1 participant reported normal, 2 participants had corrected-to-normal vision, and none of them reported color vision deficiencies. All participants were right-handed and their right eye was the dominant one. We also collected information about their prior experience with HMD-based VR systems: 2 participants had used them more than 5 times, and 1 participant had used them between 1-3 times. None of the participants were daily VR users.

3.2 Apparatus

In this study, we used an Oculus Quest 2 as HMD for our VR system, with a resolution of 1920 x 1832 pixels and a diagonal field-of-view of 110°. Participants could interact with targets using the embedded hand-tracking feature of the HMD. We tape-measured all displayed target distances and target sizes to verify that they matched the real-world distances. We created an interactive panel (Figure 2 (a)) for selecting the experiment data, such as participant number, day of the experiment, dominant hand of the participant, training strategy, and height adjustment setup so that they could comfortably execute the task. The information screen summarizes the current state of these selections for the experiment (2 (b)).

3.3 Virtual Task

We designed the virtual environment using Unity 2019.2. The participants were shown a white cursor attached to the index fingertip of their virtual hand, which allowed them to interact with virtual entities (Fig. 2 (c)) and a matrix of 5 x 6 (5 rows and 6 columns) virtual spheres, where targets were separated 6 cm from each other (Fig. 2 (d)). The virtual task involved 3 target sizes: small, medium, and large (12, 30, and 42 mm diameter, respectively).

At the beginning of the experiment, all spheres were displayed in grey except one, which was shown in yellow, indicating the current target that the participants needed to "hit" with their index finger. When the virtual cursor controlled by the participant was located inside a sphere, the sphere was highlighted in blue. If the participant continued pressing the current blue sphere, this target would be selected. After the selection, the color of the blue sphere was adjusted based on the correctness of the task execution (i.e., if they missed the correct sphere or not) to provide visual feedback. If the participant did not hit the target, the selected sphere turned red with an error sound, and the trial was recorded as a "miss". If participants "hit" the target, the color of the sphere turned green.

After each selection, the software automatically picked the next target among the available spheres and showed that sphere in yellow. That next target was chosen at random, but always in accordance with specific target distances and directions. We used 3 different target steps (second, third, and fourth targets) and varied user movement in 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 12 cm, 18 cm and 24 cm target distances. For the diagonal directions, the software also selected the second, third and fourth targets along one of the diagonals, corresponding to 16.97 cm, 25.45 cm and 33.94 cm target distances. To describe this in more compact form, we use a notation that combines the next target direction with the selected target order, e.g., "N3" represents the third target above the previous target. In total, we had 24 factor levels for 8 different directions with 3 different step sizes: North West (NW2, NW3 and NW4), South West (SW2, SW3 and SW4), South East (SE2, SE3 and SE4), North East (NE2, NE3 and NE4), North (N2, N3 and N4), West (W2, W3 and W4), South (S2, S3 and S4), and East (E2, E3 and E4). The software automatically looked for a random potential next target under the above-mentioned restrictions, while still staying within the grid and also avoiding the assignment of a target that had been used before. Participants repeated each direction and distance 2 times in each trial. To reduce potential participant confusion, the visual cues of the previous selections (red or green) were only displayed for another two selections, then each sphere turned back to grey.

3.4 Experiment Procedure

The experiment was spread across a total of 12 days with 12 sessions: a pre-training assessment session on day 1, 10 days of training sessions with a specific task execution strategy, and a final post-training session on day 12. This experimental design enables us to investigate the impact of 10-day training sessions with different task execution strategies on motor learning.

Every participant was assigned to a single, specific task execution strategy: speed-focus, accuracy-focus, or no-focus. For the speed-focus strategy, they were instructed to select the target "as fast as possible". For the accuracy-focus strategy, they were instructed to select the targets as close to their center as possible. Participants in the control group were not given any specific strategy, i.e., only instructed to complete the tasks, which is referred to as the no-focus strategy from now on. During the experiments, the experimenter observed the participants and, as needed, reminded them to follow the task execution strategy that they were assigned to.

On day 1, participants were initially asked to fill out a demographics questionnaire. Then, the experimenter demonstrated to each participant how to execute the experiment task. After the task on day 12, they were also asked to fill out a user-preference questionnaire. Each experimental session took approximately 20 minutes. Each day, we adjusted the inter-pupillary distance of the HMDs for each participant.

3.5 Experimental Design & Evaluation Metrics

We used a between-participants design with 3 task execution strategies ($3_{ExecutionStrategy}$: speed, accuracy, and no focus). To vary the ID, we used 3 different target sizes ($3_{TargetSize}$: 12, 30, and 42 mm) and 6 target distances ($3_{TargetStepSize}$: second, third, fourth). For each of the 8 directions, participants repeated 2 selections. In total, each participant performed 144 selections ($3_{TargetSize}$ x $3_{TargetStepSize}$ x 8 directions x 2 times) per day.

To analyze the motor performance, we collected data for time (s), error rate (%), throughput (bits/s), accuracy, and precision (bits).

4 Results

To analyze the pre- and post- training results, we used SPSS 24. We considered the data to be normal when the Skewness (S) and Kurtosis (K) of the data distribution were within ±1.5 [24, 39]. Otherwise, we used log-transform. If the data was not normally distributed after the log-transform, we used a Wilcoxon signed-rank test. The graphs shown in the figures below represent the mean, and the error bars represent the standard error of the mean. Similarly, the results in the table show the mean and standard error of the mean.

4.1 Pre- and Post-Training Sessions

According to the statistical data analysis, time (S = 0.12, K = -0.56), throughput (S = 0.955, K = 1.018), and ID_e (S = -0.24, K = 0.419) were normally distributed. Error rate (S = 0.929, K = -0.89) was normally distributed after log-transform. SDx was not normally distributed even after log-transform, so we used the Wilcoxon signed-rank test. The results are given in Fig. 3.

Time: Execution time results were significantly smaller during the post-training compared to the pre-training for the speed-focus participant. This participant's average time decreased from 0.8s to 0.61s. There were no statistical differences for the other two participants in execution time. Results are shown in Table 1.

Table 1: Time Results

Participant	Pre-training	Post-training	t-test
No-focus	1.10 (±0.05)	1.09 (±0.04)	t(17)=0.519, p=0.305
Accuracy-focus	1.13 (±0.03)	1.1048 (±0.03)	t(17)=1.163, p=0.13
Speed-focus	0.8 (±0.02)	0.61 (±0.01)	t(17)=14.306, p<0.01

Error rate: Error rate results were significantly lower during the post-training compared to the pre-training for the no-focus participant. This participant decreased their error rate from an average of 0.099% to 0.021%. There were no statistical significance for the other two participants in terms of the error rate. The results are shown in Table 2.

Throughput: Throughput results were significantly greater during the post-training compared to the pre-training for all three participants. The results are shown in Table 3.

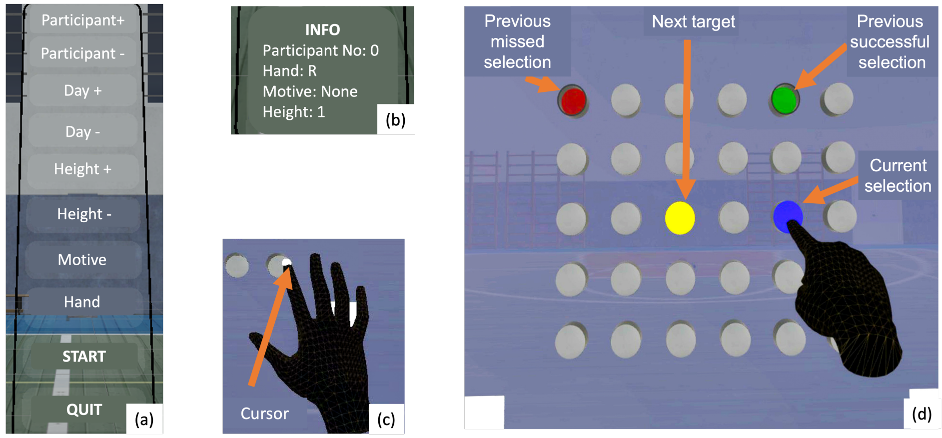

Figure 2: VR system interaction: (a) Interaction panel used to select the configuration for the experiment for each participant and experiment conditions. (b) An information screen summarizing the selections from the interaction panel. (c) The participant saw a white cursor placed at the fingertip of a hand avatar. (d) An annotated screenshot how a participant saw the virtual task in the HMD. In the task, they interacted with a 5x6 grid of spheres all shown in grey by default. The yellow sphere shows the next target, while blue indicates that the cursor is inside a sphere, and that if the participant continued the selection process, this target would be selected. A red sphere shows a previously missed target, while green shows a previously correctly selected target.

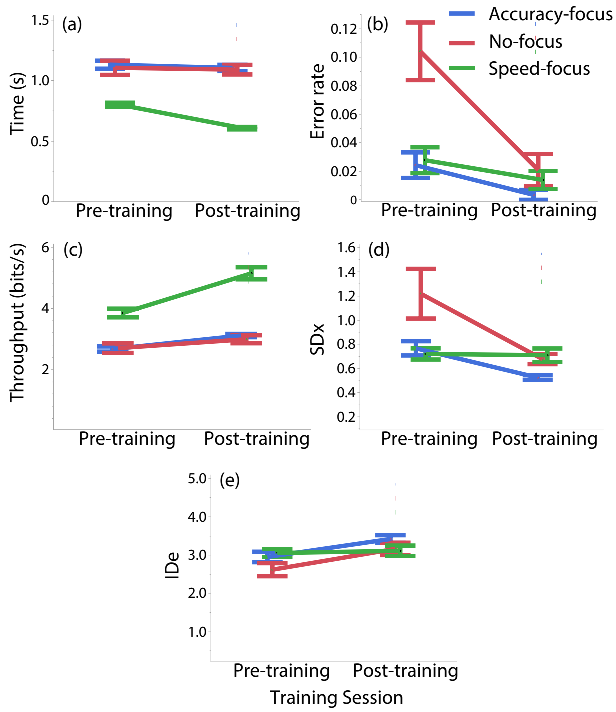

Figure 3: Pre- and post-training comparison of IDe for (a) time, (b) error rate, (c) throughput, (d) *SDx*, and (e) *IDe*.

Table 2: Error Rate Results

Participant	Pre-training	Post-training	t-test
No-focus	0.099 ($\pm$0.021)	0.021 ($\pm$0.011)	t(17)=5.048, p<0.001
Accuracy-focus	0.024 ($\pm$0.008)	0.0034 ($\pm$0.003)	t(17)=-0.941, p=0.18
Speed-focus	0.027 ($\pm$0.009)	0.013 ($\pm$0.006)	t(17)=1.068, p=0.15

Table 3: Throughput Results

Participant	Pre-training	Post-training	t-test
No-focus	2.70 ($\pm$0.15)	2.99 ($\pm$0.13)	t(17)=-2.149, p<0.5
Accuracy-focus	2.67 ($\pm$0.08)	3.11($\pm$0.05)	t(17)=-5.511, p<0.01
Speed-focus	3.85 ($\pm$0.14)	5.14 ($\pm$0.19)	t(17)=-6.562, p<0.01

SDx : *SDx* results were significantly lower during the post-training compared to the pre-training for the no-focus and accuracy-focus participants. The no-focus participant's accuracy improved from 1.21 to 0.67, and the accuracy-focus participant's accuracy improved from 0.76 to 0.52. There were no significant differences for the speed-focus participant in terms of the *SDx*. The results are shown in Table 4.

Table 4: SDx Results

Participant	Pre-training	Post-training	Z-test
No-focus	1.21 ($\pm$0.2)	0.67 ($\pm$0.04)	Z=-3.5, p<0.001
Accuracy-focus	0.76 ($\pm$0.06)	0.52 ($\pm$0.02)	Z=3.41, p<0.001
Speed-focus	0.72 ($\pm$0.04)	0.71 ($\pm$0.06)	Z=-849, p=396

IDe : *IDe* results were significantly greater during the post-training compared to the pre-training for the no-focus and accuracy-focus participants. The no-focus participant's precision increased from 2.61 bits to 3.16 bits, and the accuracy-focus participant's precision increased from 2.95 bits to 3.42 bits. There were no significant differences for the speed-focus participant in terms of the *IDe*. The results are shown in Table 5.

4.2 Longitudinal Study Results

We also looked at the longitudinal results to observe details of the motor performance changes for each participant over time. As visible in the plots in Fig. 4, we did not observe major anomalies.

Table 5: IDe Results

Participant	Pre-training	Post-training	t-test
No-focus	2.61 ($\pm$0.17)	3.16 ($\pm$0.16)	$t(17)=-4.098$, $p<0.001$
Accuracy-focus	2.95 ($\pm$0.13)	3.42($\pm$0.09)	$t(17)=-5.523$, $p<0.001$
Speed-focus	3.05 ($\pm$0.14)	3.11 ($\pm$0.19)	$t(17)=-0.554$, $p=0.293$

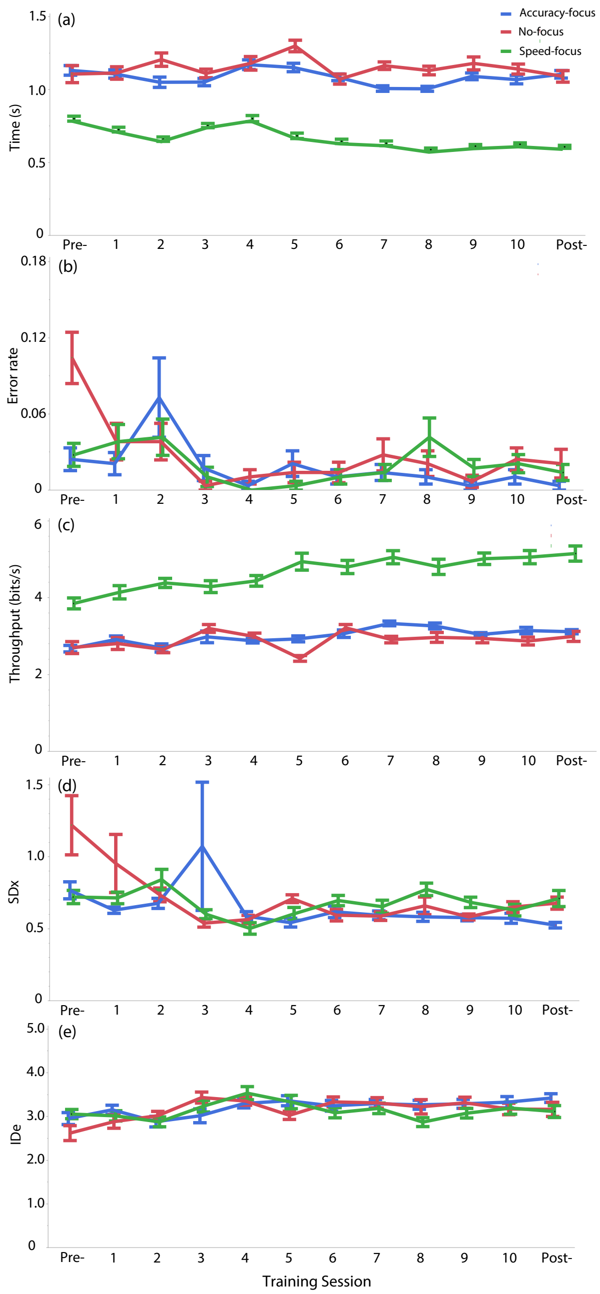

Figure 4: Longitudinal study results for (a) time, (b) error rate, (c) throughput, (d) SDx, and (e) IDe.

4.3 Questionnaire Results

After the training session on day 12, we also asked participants about their insights on HMD-based VR EHCTS. We first asked them if they felt any improvement in their performance during the training sessions (1- I do not feel improvement, 7- I feel improvement), and they reported to have mostly felt an improvement in their skills, with an average rating of 6. We also asked participants how much they felt annoyed with the system (1-I do not feel annoyed at all, 7- I am extremely annoyed). The participants reported not to have been annoyed with the HMD-based VR EHCTS, with an average of 3.6 $\pm$1.46. We finally asked about their physical fatigue (1- I feel rested, 7- I feel extremely fatigued), and the average rating was 4.6 $\pm$1.4, indicating some (albeit limited) fatigue, which is unsurprising after a longitudinal training session. Additionally, one participant mentioned, "While performing in a VR environment, it feels more vibrant and the experiment makes you feel more complete and focused."

5 Discussion

In this paper, we asked three participants to use an HMD-based VR EHCTS while focusing either on speed, accuracy, or no assessment criterion and observed the change in their performance. Our results revealed that each participant improved their motor performance after 10 days of training. However, as can be seen from the results for time, we only observed significantly lower execution time for the speed-focus participant. Thus, users who want to focus on reducing their execution time should only focus on their speed in EHCT setups. After all, such systems are also known as reaction-time training systems, which aim to lower the time to react to stimuli.

Beyond increasing the speed, another purpose of EHCTSs is to improve the eye-hand coordination of the users. Unlike the speed-focus participant, the accuracy-focus participant showed significant improvements in both accuracy and precision. This result also supports the findings of previous work [4], where participants' accuracy only increased when they focused on accuracy.

Our results imply that participants should focus on specific assessment criteria to improve their corresponding performance. In the meantime, their other psychomotor skills can still improve, which plays a vital role in eye-hand coordination tasks [17, 27]. Thus, our results support **H1. different task execution strategies have a different impact on long-term user performance for HMD-based VR EHCTSs**.

When we look at the effective throughput results, we observe that participants' motor skills improvements also affected their throughput performance. For each assessment criterion, we observed an increase in throughput, which could be potentially related to time, accuracy, or precision results. For a trainer, such an assessment method could decrease their workload since it could potentially help them to monitor the *overall* motor performance increase of a trainee. Thus, this result also supports our hypothesis, **H2. it is possible to use effective throughput as a long-term assessment criterion for HMD-based VR EHCTSs**.

In summary, if a trainee wants to improve their reaction time, they should focus on executing the task as fast as possible. Still, any performance improvement should also be visible in the throughput progress of the participant. However, the performance of the trainee in terms of accuracy, precision, and error rate might not improve. If a trainee wants to improve their accuracy or precision, they should focus on accuracy, and this would also be visible in the effective throughput. Finally, if a trainee does not focus on a specific task execution strategy, their error rate, accuracy, and precision performance might improve, and this would still be visible in the effective throughput results. Thus, it is important to plan the task execution strategy ahead of the training sessions to improve user performance in HMD-based VR EHCTSs. In addition, our questionnaire findings reveal that all participants enjoyed the HMD-based VR EHCTS and self-observed an increase in their task performance in our longitudinal study.

Even though our results support the approach of using effective throughput as an assessment criterion, trainers should be careful when they monitor user performance while looking only at this particular measure. After all, using only effective throughput decreases the expressivity of motor skills monitoring. Thus, it is vital to also keep track of individual performance criteria, i.e., time, accuracy, or precision, and draw corresponding conclusions based on a more holistic understanding. We thus suggest making all decisions not solely based on effective throughput.

5.1 Limitations & Future Work

In this study, participants were asked to focus on a particular assessment criterion, and if they did not follow that particular criterion, the experimenter reminded them to do so. However, we observed a few cases where the participants failed to follow the instructions, such as the accuracy-focus participant on day 2 in terms of the error rate. For future studies, we recommend more immediate verbal feedback to help participants to focus on a particular task execution strategy.

We deliberately asked participants not to focus on effective throughput as an assessment criterion since we are aware of previous work that challenges the invariance of MacKenzie's effective throughput [47]. In the current paper, we did not analyze the participants' speed-accuracy trade-off in detail, since the number of participants was not high enough to draw any specific conclusions.

We only used an HMD-based VR system to investigate longitudinal performance in EHCTS. Yet, previous work showed that user performance can significantly decrease with HMD-based AR systems [9] and thus suggested not using them for EHCT. In their work, the authors used a Meta 2 HMD for visual feedback and a Leap Motion for hand tracking. As AR technologies have improved since then, we also suggest investigating HMD-based AR EHCTS and extending our studies to other devices and virtual environments.

The effects of movement direction on user performance have already been examined by previous Fitts' law and human motor performance studies, such as [4, 8, 32, 33, 53]. Our findings are consistent with those in the previous literature. Additionally, when they reach for farther away targets, their movement time increases and their accuracy decreases [22,48,59]. Given this, and that we used on a small number of participants, we did not analyze movement direction in detail in this study.

Another limitation of this work is the variety of task execution strategies. While we asked participants to complete the tasks focusing on speed, accuracy, or no focus, we could have investigated other strategies, such as precision (i.e., selecting the targets always at the same position—not necessarily at the center of the target) or error rate (i.e., reducing the number of errors). We recommend that future work thus investigate other task execution strategies.

Moreover, in this paper, we did not focus on the interaction between different task execution strategies. The number of participants (3) was also clearly not enough to conduct a between-subjects analysis. However, we invite researchers to conduct additional studies to analyze the effect of different task execution strategies in EHCTSs, to potentially reveal optimal training plans.

6 Conclusion

In this paper, we asked three participants to perform eye-hand coordination training in a HMD-based VR system for 12 days in a longitudinal study. While performing the task, each participant focused on a specific task execution strategy, i.e., one participant focused on speed, another on the accuracy, and the third participant was not given a specific focus. The results showed that each task execution strategy has a different effect on one or more psychomotor characteristics of the trainee, which highlights the importance of the training program. We also showed that effective throughput is a candidate for monitoring the overall motor performance progress in eye-hand coordination training systems.

In the future, this proposed study should be extended to HMD-based AR systems as well as a conventional eye-hand coordination training system, involving additional task strategies, and more participants to accurately compare the improvements with different task execution strategies.

References

[1] K. Ahir, K. Govani, R. Gajera, and M. Shah. Application on virtual reality for enhanced education learning, military training and sports. *Augmented Human Research*, 5(1):1–9, 2020.

[2] M. D. Barrera Machuca and W. Stuerzlinger. Do stereo display deficiencies affect 3D pointing? In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, p. LBW126. ACM, 2018.

[3] M. D. Barrera Machuca and W. Stuerzlinger. The effect of stereo display deficiencies on virtual hand pointing,. In *2019 CHI Conference on Human Factors in Computing Systems*, p. 14 Pages. ACM, 2019.

[4] A. U. Batmaz. *Speed, precision and grip force analysis of human manual operations with and without direct visual input*. PhD thesis, Strasbourg, 2018.

[5] A. U. Batmaz, M. D. Barrera Machuca, J. Sun, and W. Stuerzlinger. The effect of the vergence-accommodation conflict on virtual hand pointing in immersive displays. In *Conference on Human Factors in Computing Systems*, CHI '22, May 2022.

[6] A. U. Batmaz, M. de Mathelin, and B. Dresp-Langley. Getting nowhere fast: trade-off between speed and precision in training to execute image-guided hand-tool movements. *BMC psychology*, 4(1):55, 2016.

[7] A. U. Batmaz, M. de Mathelin, and B. Dresp-Langley. Seeing virtual while acting real: Visual display and strategy effects on the time and precision of eye-hand coordination. *PloS one*, 12(8):e0183789, 2017.

[8] A. U. Batmaz, M. de Mathelin, and B. Dresp-Langley. Effects of image size and structural complexity on time and precision of hand movements in head mounted virtual reality. In *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 167–174, March 2018. doi: 10.1109/VR.2018.8446217

[9] A. U. Batmaz, A. K. Mutasim, M. Malekmakan, E. Sadr, and W. Stuerzlinger. Touch the wall: Comparison of virtual and augmented reality with conventional 2d screen eye-hand coordination training systems. In *Conference on Virtual Reality and 3D User Interfaces*, VR '20, pp. 184–193. IEEE, Mar 2020. doi: 10.1109/VR46266.2020.1581205539914

[10] A. U. Batmaz and W. Stuerzlinger. Effective throughput analysis of different task execution strategies for mid-air fitts' tasks in virtual reality. *Transactions on Visualization and Computer Graphics*, Oct 2022. doi: 10.1109/TVCG.2022.3203105

[11] A. U. Batmaz, X. Sun, D. Taskiran, and W. Stuerzlinger. Hitting the Wall: Mid-air interaction for eye-hand coordination. In *25th ACM Symposium on Virtual Reality Software and Technology*, VRST '19, pp. 30:1–30:5. ACM, New York, NY, USA, 2019.

[12] A. U. Batmaz, S. Xintian, D. Taskiran, and W. Stuerzlinger. Eye-hand coordination training for sports with mid-air vr. In *26th Symposium on Virtual Reality Software and Technology*, VRST '20. ACM, Nov 2020.

[13] B. Bideau, R. Kulpa, N. Vignais, S. Brault, F. Multon, and C. Craig. Using virtual reality to analyze sports performance. *IEEE Computer Graphics and Applications*, 30(2):14–21, 2009.

[14] A. T. Biggs, D. J. Geyer, V. M. Schroeder, F. E. Robinson, and J. L. Bradley. Adapting virtual reality and augmented reality systems for naval aviation training. Technical report, Naval Medical Research Unit Dayton, 2018.

[15] J. Boritz and K. S. Booth. A study of interactive 3d point location in a computer simulated virtual environment. In *Proceedings of the ACM symposium on Virtual reality software and technology*, pp. 181–187, 1997.

[16] K. Burris, K. Vittetoe, B. Ramger, S. Suresh, S. T. Tokdar, J. P. Reiter, and L. G. Appelbaum. Sensorimotor abilities predict on-field performance in professional baseball. *Scientific reports*, 8(1):1–9, 2018.

[17] A. Covaci, C. Postelnicu, A. N. Panfir, and D. Talaba. A virtual reality simulator for basketball free-throw skills development. In *Doctoral Conference on Computing, Electrical and Industrial Systems*, pp. 105–112. Springer, 2012.

[18] A. V. L. De Araújo, J. F. d. O. Neiva, C. B. d. M. Monteiro, and F. H. Magalhães. Efficacy of virtual reality rehabilitation after spinal cord

injury: a systematic review. *BioMed research international*, 2019, 2019.

[19] Dynavision International, 2019.

[20] H. Engelbrecht, R. Lindeman, and S. Hoermann. A swot analysis of the field of virtual reality for firefighter training. *Frontiers in Robotics and AI*, 6:101, 2019.

[21] G. B. Erickson, K. Citek, M. Cove, J. Wilczek, C. Linster, B. Bjarnason, and N. Langemo. Reliability of a computer-based system for measuring visual performance skills. *Optometry-Journal of the American Optometric Association*, 82(9):528–542, 2011.

[22] P. M. Fitts. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology*, 47(6):381, 1954.

[23] K. L. Gao, S. S. Ng, J. W. Kwok, R. T. Chow, and W. W. Tsang. Eye–hand coordination and its relationship with sensori-motor impairments in stroke survivors. *Journal of rehabilitation medicine*, 42(4):368–373, 2010.

[24] J. F. Hair Jr, W. C. Black, B. J. Babin, and R. E. Anderson. Multivariate data analysis, 2014.

[25] J. A. Harpham, J. P. Mihalik, A. C. Littleton, B. S. Frank, and K. M. Guskiewicz. The effect of visual and sensory performance on head impact biomechanics in college football players. *Annals of Biomedical Engineering*, 42(1):1–10, Jan 2014. doi: 10.1007/s10439-013-0881-8

[26] C. Huang, Y. Zhang, C. Zhu, C. Zhang, and H. Meng. Chinese sports basketball teaching tactics training system combined with multimedia interactive model and virtual reality technology. *Multimedia tools and applications*, pp. 1–15, 2019.

[27] Y. Huang, L. Churches, and B. Reilly. A case study on virtual reality american football training. In *Proceedings of the 2015 Virtual Reality International Conference*, p. 6. ACM, 2015.

[28] ISO 9241-411:2012. Ergonomics of human-system interaction – part 411: Evaluation methods for the design of physical input devices. ISO, May 2012.

[29] C. Jin, L. Dai, and T. Wang. The application of virtual reality in the training of laparoscopic surgery: a systematic review and meta-analysis. *International Journal of Surgery*, 87:105859, 2021.

[30] A. K. Mutasim, W. Stuerzlinger, and A. U. Batmaz. Gaze tracking for eye-hand coordination training systems in virtual reality. Extended Abstract, Apr 2020. doi: 10.1145/3334480.3382924

[31] J. W. Keogh and P. W. Winwood. The epidemiology of injuries across the weight-training sports. *Sports medicine*, 47(3):479–501, 2017.

[32] C. J. Lin, H. Chen, P. Cheng, and T. Sun. Effects of displays on visually controlled task performance in three-dimensional virtual reality environment. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 25(5):523–533, 2015. doi: 10.1002/hfm.20566

[33] R. F. Lin and H. Cheng. Accessing effects of various depth-cue combinations on hand control movement in a virtual environment. In M. Kurosu, ed., *Human-Computer Interaction. Novel User Experiences*, pp. 527–537. Springer International Publishing, Cham, 2016.

[34] X. Liu, J. Zhang, G. Hou, and Z. Wang. Virtual reality and its application in military. *IOP Conference Series: Earth and Environmental Science*, 170(3):032155, 2018.

[35] T. Luger, T. Bosch, M. Hoozemans, M. de Looze, and D. Veeger. Task variation during simulated, repetitive, low-intensity work–influence on manifestation of shoulder muscle fatigue, perceived discomfort and upper-body postures. *Ergonomics*, 58(11):1851–1867, 2015.

[36] I. S. MacKenzie and W. Buxton. Extending fitts' law to two-dimensional tasks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '92, p. 219–226. Association for Computing Machinery, New York, NY, USA, 1992. doi: 10.1145/142750.142794

[37] I. S. MacKenzie and P. Isokoski. Fitts' throughput and the speed-accuracy tradeoff. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '08, p. 1633–1636. Association for Computing Machinery, New York, NY, USA, 2008. doi: 10.1145/1357054.1357308

[38] I. S. MacKenzie and A. Oniszczak. A comparison of three selection techniques for touchpads. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 336–343. ACM Press/Addison-Wesley Publishing Co., 1998.

[39] P. Mallery and D. George. SPSS for windows step by step: a simple guide and reference. *Allyn, Bacon, Boston,*, 2003.

[40] Meyend. Meyend training, September 2022.

[41] A. Miah, A. Fenton, and S. Chadwick. Virtual reality and sports: The rise of mixed, augmented, immersive, and esports experiences. In *21st Century Sports*, pp. 249–262. Springer, 2020.

[42] S. C. Michalski, A. Szpak, D. Saredakis, T. J. Ross, M. Billinghurst, and T. Loetscher. Getting your game on: Using virtual reality to improve real table tennis skills. *PloS one*, 14(9):e0222351, 2019.

[43] H. C. Miles, S. R. Pop, S. J. Watt, G. P. Lawrence, and N. W. John. A review of virtual environments for training in ball sports. *Computers & Graphics*, 36(6):714 – 726, 2012. doi: 10.1016/j.cag.2012.04.007

[44] E. Nagorsky and J. Wiemeyer. The structure of performance and training in esports. *PloS one*, 15(8):e0237584, 2020.

[45] NIKE-SPARQ. Nike introduces SPARQ Sensory Performance (SSP), October 2011.

[46] H. Oagaz, B. Schoun, and M.-H. Choi. Performance improvement and skill transfer in table tennis through training in virtual reality. *IEEE Transactions on Visualization and Computer Graphics*, 2021.

[47] H. B. Olafsdottir, Y. Guiard, O. Rioul, and S. T. Perrault. A new test of throughput invariance in Fitts' law: Role of the intercept and of Jensen's inequality. In *Proceedings of the 26th Annual BCS Interaction Specialist Group Conference on People and Computers*, BCS-HCI '12, p. 119–126. Swindon, GBR, 2012.

[48] E. W. Pedersen and K. Hornbæk. An experimental comparison of touch interaction on vertical and horizontal surfaces. In *Proceedings of the 7th Nordic Conference on Human-Computer Interaction: Making Sense Through Design*, NordiCHI '12, pp. 370–379. ACM, New York, NY, USA, 2012. doi: 10.1145/2399016.2399074

[49] D. Poltavski and D. Biberdorf. The role of visual perception measures used in sports vision programmes in predicting actual game performance in division i collegiate hockey players. *Journal of sports sciences*, 33(6):597–608, 2015.

[50] Quotronics Limited. Batak fitness training solutions, 2019.

[51] B. M. Schout, A. Hendrikx, F. Scheele, B. L. Bemelmans, and A. Scherpbier. Validation and implementation of surgical simulators: a critical review of present, past, and future. *Surgical endoscopy*, 24(3):536–546, 2010.

[52] J. Shepherd, L. Carter, G. Pepping, and L. Potter. Towards an operational framework for designing training based sports virtual reality performance simulators. In *Multidisciplinary Digital Publishing Institute Proceedings*, vol. 2, p. 214, 2018.

[53] B. N. Smetanin and K. E. Popov. Effect of body orientation with respect to gravity on directional accuracy of human pointing movements. *European Journal of Neuroscience*, 9(1):7–11, 1997. doi: 10.1111/j.1460-9568.1997.tb01347.x

[54] E. M. Staurset and E. Prasolova-Førland. Creating a smart virtual reality simulator for sports training and education. In *Smart Education and e-Learning 2016*, pp. 423–433. Springer, 2016.

[55] J. A. Stone, B. W. Strafford, J. S. North, C. Toner, and K. Davids. Effectiveness and efficiency of virtual reality designs to enhance athlete development: an ecological dynamics perspective. *Movement & Sport Sciences-Science & Motricité*, 4(102):51–60, 2018.

[56] R. J. Teather, A. Pavlovych, W. Stuerzlinger, and I. S. MacKenzie. Effects of tracking technology, latency, and spatial jitter on object movement. In *3D User Interfaces, 2009. 3DUI 2009. IEEE Symposium on*, pp. 43–50. IEEE, 2009.

[57] E. Verdaasdonk, J. Dankelman, J. Lange, and L. Stassen. Incorporation of proficiency criteria for basic laparoscopic skills training: how does it work? *Surgical endoscopy*, 22(12):2609–2615, 2008.

[58] L. Wang, K. Krasich, T. Bel-Bahar, L. Hughes, S. R. Mitroff, and L. G. Appelbaum. Mapping the structure of perceptual and visual–motor abilities in healthy young adults. *Acta psychologica*, 157:74–84, 2015.

[59] T. Whisenand and H. Emurian. Analysis of cursor movements with a mouse. *Computers in Human Behavior*, 15(1):85 – 103, 1999. doi: 10.1016/S0747-5632(98)00036-3

[60] Y. Zhang, H. Liu, S.-C. Kang, and M. Al-Hussein. Virtual reality applications for the built environment: Research trends and opportunities. *Automation in Construction*, 118:103311, 2020.