Investigating Augmented Reality for Adaptive Motor-Skill Training

Dishita Turakhia
MIT CSAIL
Cambridge, USA
dishita@mit.edu

Mark Parent
Reality Labs Research
Toronto, Canada
mrkprnt@gmail.com

Tovi Grossman
University of Toronto
Toronto, Canada
tovi@dgp.toronto.edu

Michael Glueck
Reality Labs Research
Toronto, Canada
mglueck@meta.com

Ben Lafreniere
Reality Labs Research
Toronto, Canada
ben.lafreniere@gmail.com

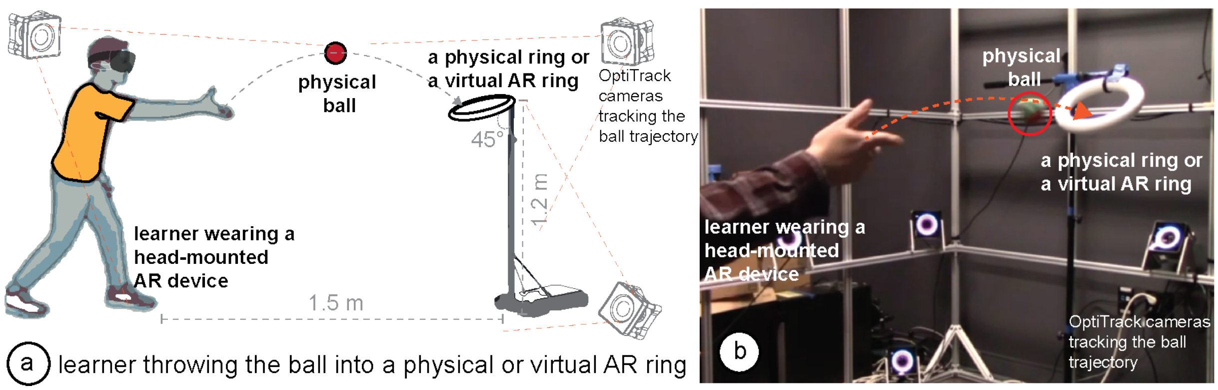


Figure 1: This work explores using augmented reality (AR) to adapt functional task difficulty for motor-skill training. We built a prototype AR adaptive training system and a conducted user study (N=16), where (a) participants trained to throw a ball into a physical ring. (b) For the training, participants wore a head-mounted display and practiced throwing the physical ball into a virtual ring that either maintained its diameter or dynamically changed diameter based on their skill level to make the task more or less difficult.

ABSTRACT

Adaptive training of motor-skills, where the difficulty level of the training task is adapted optimally based on the learner's skill levels, has been shown to enable higher learning gains compared to non-adaptive training. However, prior approaches rely on adapting *physical* tools that are tedious to design and build. This work investigates using augmented reality (AR) to achieve a similar objective of maintaining functional task difficulty – the difficulty experienced by the learner – at an optimal challenge point during adaptive training. A study prototype of an AR adaptive basketball training system was developed, wherein the learners train to throw a *physical ball* into a *virtual AR hoop* seen through a head-mounted device. Results from the study (N=16) aimed to measure the learning gains showed higher learning gains after adaptive AR training compared to non-adaptive AR training. An analysis of participant feedback, however, highlighted challenges with AR-based adaptive training, pointing to the need for a different design approach compared to the physical adaptive tools. Collectively, this exploratory study investigates the use of AR for adaptive motor-skill learning and lays the foundation for future research directions for the AR-tool design.

GI '25, May 26–29, 2025, Kelowna, BC

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

CCS CONCEPTS

• **Human-centered computing → Mixed / augmented reality**; **User studies**.

KEYWORDS

motor skill learning, adaptive learning, functional task difficulty, augmented reality

ACM Reference Format:
Dishita Turakhia, Mark Parent, Tovi Grossman, Michael Glueck, and Ben Lafreniere. 2025. Investigating Augmented Reality for Adaptive Motor-Skill Training. In *Proceedings of Graphics Interface (GI '25)*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Learning motor skills is an essential part of human development, and an extensive body of research has developed tools for this purpose, including for skills such as riding a bike [3, 66], complex movements in sports such as basketball [5, 48, 62], and physiotherapy training and muscle rehabilitation [9, 42]. Various approaches to supporting motor skill learning have also been investigated, including varying instructional guidance [7], feedback [63], or task support provided during training [33].

This work looks at one such approach, which is to optimize *functional task difficulty*, i.e., the level of challenge experienced by learners during training, based on the learner's current skill level [32]. Studies show that such adaptive motor skill training leads to higher learning gains compared to non-adaptive training [26]. Recent research has demonstrated the learning benefits of implementing this approach by *physically* adapting training tools to adjust functional task difficulty based on learner performance [64]. For example, when training to throw a ball into a hoop, the difficulty of the task can be adapted by adjusting the size and height of the hoop to match the level of skill of the learner. The physical tool adaptation approach has been shown to be flexible to support a wide variety of different motor skills, such as skateboarding, balancing a wobble-board, and training for golf [65].

Adaptation using physical tools, however, has inherent constraints, such as the cost and complexity of designing and building physical tools, slow adaptation, and the possibility that tools break during use. With this as motivation, the present work investigates the possibility of adaptively optimizing functional task difficulty using *virtual* training tools in Augmented Reality (AR). Unlike physical tools, virtual content presented in AR is not subject to many of the limitations on physical tools. The promise is that AR could make adaptive motor skills training more accessible.

To investigate this possibility, an exploratory study of motor skill training using adaptive AR tools that adapt the functional task difficulty was conducted. An adaptive hoop for a ball-throwing task was developed (Figure 1) inspired by the seminal research study on variable motor skill learning by Kerr and Booth [34]. The training system tracked the physical ball's trajectory, monitored the learner's performance (using OptiTrack), and adapted the diameter of a virtual hoop, displayed in AR via a Head Mounted Display (using HoloLens2), to match the user's skill level. A between-subjects user study with 16 participants was conducted to compare the performance improvements after training using an adaptive AR hoop (that changed its diameter) versus a non-adaptive AR hoop. Participant feedback was collected to further identify the challenges and opportunities of designing adaptive tools in AR.

Our findings revealed that training with the adaptive AR tool led to marginally higher learning gains compared non-adaptive AR tools. However, the adaptive AR tools also created significant new design challenges, such as the absence of interaction cues between physical and virtual objects, which impacted task performance and skill transfer. Using AR to implement adaptive motor-skill training thus requires a new set of design strategies as compared to physical tool adaptation. We discuss avenues for future research and design opportunities to adapt the functional task difficulty in AR training tools as the AR technology advances.

In summary, this paper contributes to the design of AR-based training tools through:

- A between-subjects exploratory study on training using an adaptive AR tool that optimally adjusts the functional task difficulty, which revealed the need for a distinct design paradigm for adapting tools in AR compared to physical counterparts.
- A thematic analysis of participant feedback to identify (a) the design challenges in adapting tools in AR, including the absence of interaction cues between virtual and physical objects; (b) design opportunities for adapting training tools in AR, using visualization overlays, and spatial, sensory, and temporal cues.

2 RELATED WORK

We begin this section with a background on pedagogical frameworks for adaptive motor skills training, particularly for varying the functional task difficulty to maintain optimal challenge during training. We then discuss the related systems designed for adaptive training using both physical and virtual AR tools and highlight the unexplored approach of using shape-change in virtual training tools. We also highlight this gap through a discussion on the design of AR training systems that use features like multimodal feedback and instructions for learning, and point to the gap in exploring the design of virtual shape-adaptation in AR and its impact on learning.

2.1 Adaptive Motor Skill Learning

Research on motor skill learning [51, 53] highlights that task difficulty significantly impacts training outcomes [22]. Tasks that are too easy underchallenge learners, while overly difficult ones overwhelm them, limiting learning potential. Kelly [32] introduced the concept of adaptive training, which dynamically adjusts task parameters based on learner performance, ensuring task difficulty aligns with the learner's capabilities for optimal learning. Effective adaptive training requires components such as performance measurement, auto-adaptation logic, error calculation, and task difficulty adjustment. Adapting functional task difficulty offers benefits like scalable, personalized learning but remains challenging to automate [1, 2, 32]. Although various models evaluate motor skill learning [22, 24, 44, 55, 68], their application in automated systems is still in its infancy, as discussed in the next subsection.

2.2 Adaptive Training Systems for Motor Skills

Prior HCI research has proposed adaptive training systems that offer personalized and self-directed learning by adapting instructions, guidance, or feedback during training [16, 32]. Examples include De Kok et al.'s system, which uses video analysis to tailor squat instructions[19], Park and Lee's *Motion Echo Snowboard*, which adjusts visual feedback for balance training [47], and Yamaoka et al.'s *dePENd*, which uses magnetic support for guided path tracing [69]. While these systems emphasize personalized instruction, they often overlook adapting functional task difficulty – a promising approach where task difficulty dynamically adjusts to keep learners at an optimal challenge level [26]. Building on this approach, researchers designed tools like an adaptive basketball hoop that adjusts height and width based on performance, improving motivation and outcomes compared to static or manually adaptive methods [64]. This concept extends to adaptive training tools for skills like bike riding, walking, and balancing a wobbleboard [65], as well as *DigituSync* for fine motor skills in music training [45]. Despite its potential, applying adaptive functional task difficulty in Augmented Reality (AR) for motor skill training remains largely unexplored – a gap we address by investigating adaptive AR training using a ball-throwing activity to understand its design and user experience implications.

2.3 Augmented Reality Tools for Motor Skills

The design of AR tools for motor skill learning spans diverse applications, including sports (e.g., basketball [10, 38, 46, 61], football, cycling [59], judo [15, 56], and other sports [17, 25, 41]), physical education [43, 58], rehabilitation [20, 57], and professional skills like machine assembly [28], industrial tool operation [12, 14], robot teleoperation [6], and medical surgery [50]. The design space for these AR systems leverage various technologies, such as wearables [29], hand-held devices [18], mirror-like screens [4, 36], spatial AR [30, 40], and head-mounted displays [11, 31] to scaffold training. While these diverse AR applications for motor-skill learning have explored the design space of AR tools through non-adaptive design approaches, we contribute to this existing literature by exploring and extending the design space of AR training tools using the adaptive-training framework. Currently, AR is used to scaffold learners' training mainly through adaptive instructional guidance [7]. Studies show that such adaptive tools accelerate learning [63], outperform video-assisted instruction [13], improve body movement accuracy in physiotherapy [57], increase fine motor accuracy for drawing [37], and improve techniques for rock-climbing [67]. Our research builds on this body of related work of adapting instructions using visual overlays in AR by exploring an alternative approach of adapting virtual tools in AR to scaffold learning.

2.4 Design Opportunities in Augmented Reality

AR environments offer several design affordances for adaptive training tools, with visual feedback being the most frequently used affordance. Other AR features used to support adaptive training of motor skills include auditory, haptic, or multimodal augmented feedback [21, 23, 52]. However, these systems primarily employed a correctional approach, where the system measured learners' performance and provided them with multimodal feedback on correcting their actions. For example, the *Augmented Practice Mirror* displayed visual feedback of a learner's motion on top of a teacher's to support the learning of physical motions in dance, sports, and craftmaking [36]. Similarly, *Anywhere Hoop* and Lin et al.'s virtual free throw training systems for basketball provided visual and auditory feedback via a HoloLens to improve a learner's throwing trajectory [61]. While this approach of adapting instructional feedback is explored extensively, some recent studies have also shown that frequent feedback can increase cognitive load and hinder learning [54]. This points to the need to reimagine learning in AR using alternative approaches in the future, for example by *adapting the functional task difficulty*. Motivated to investigate the use of AR for adaptive skill learning, we designed an explorative study that we detail in the following section.

3 EXPLORATORY USER STUDY

3.1 Study Goals:

To gain initial insights into the benefits and challenges of implementing adaptive motor-skill training in AR using virtual training tools, we adapted the method used in prior work by Turakhia et al. [64] to evaluate the learning gains of adaptive physical tools. Specifically, the goal was to answer the following research questions:

- **RQ1:** *How do the learning gains and experiences of adaptive AR training differ from non-adaptive AR training?*
- **RQ2:** *What additional design challenges arise when using adaptive AR training tools to adapt functional task difficulty, as compared to physical training tools?*

With these goals in mind for our study, we chose the motor skill of throwing a ball into a ring. For training the participants, we compared *AR training (adaptive and non-adaptive)* conditions (Figure 1-b) with a *control (non-adaptive physical) training* condition using a non-adaptive physical ring (Figure 1-a). To test the learning gains, we then measured their performances in *test conditions* on the non-adaptive physical ring (Figure 1-a). We calculated the differences in the performances of test conditions using a between-subjects study design and analyzed participants' feedback to examine the effects of adapting functional task difficulty in AR on their training experiences.

3.2 Participants:

16 participants (9F, 7M) with ages between 23-63 years (μ = 32 years, σ = 8.5 years) [1] with mean height 5'6" (σ = 3.5") were recruited through an open-call for the study. They had varied prior experience with ball sports ranging from never playing ball-sports (n=3), to playing 10 yrs ago (n=3), between 2 to 5 years ago (n=6), a year ago (n=2), to monthly frequency (n=2). 13 participants were right-handed and 3 participants were ambidextrous. All participants had some prior experience using either AR or VR devices (between 1.5 to 4 years).

3.3 Learning Task:

As in Turakhia et al. [64], the task was to throw a physical ball into a ring or hoop from a fixed standing position (see Figure 1). Each attempt took 3-6 seconds, which allowed for efficient data collection. The participants threw a physical ball [2] into a physical ring (for control (non-adaptive physical) and test conditions) or a virtual AR ring seen through the HoloLens (for training conditions).

To measure the learner's performance, we used OptiTrack to monitor the ball's trajectory and check if the attempt was successful (i.e., the ball went inside the ring), partially failed (i.e., the ball did not go in the ring but hit the rim), or completely failed (i.e., the ball missed the ring). We awarded 1 point per successful attempt, 0.5 points per partially failed attempt, and 0 points per completely failed attempt. In the AR setup, the AR ring changed color from white to

[1] The majority of participants were in a fairly tight age range of (25-36) with the exception of one participant aged 63 (M)

[2] In pilot studies, we experimented with throwing a virtual ball that was superimposed on the physical ball. Because the feedback indicated that it distracted learners and hindered training, we used only the physical ball for the study.

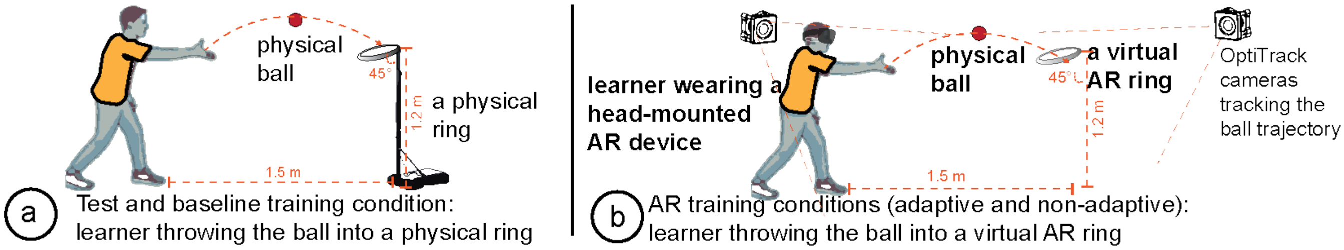


Figure 2: (a) For the study's test condition, participants trained to successfully throw a ball into a non-adaptive physical ring. For the control condition of non-adaptive physical training, the participants trained to throw a physical ball inside the physical ring (while wearing a head-mounted display (HMD) to eliminate the confounding factor of using an HMD in AR conditions) (b) For the AR training, they wore a head-mounted display and practiced throwing the ball into a virtual ring that either maintained its diameter or dynamically changed diameter based on their skill level to make the task more or less difficult.

green (1 point), or yellow (0.5 points), to red (0 points) (Figure 3). These score points were used to change the functional task difficulty by increasing or decreasing the virtual ring's diameter.

3.4 Adaptive Task Difficulty Algorithm

To determine when to adapt the virtual ring in AR, we first monitored a participant's performance by tracking the ball's trajectory and checking if the attempt was successful (i.e., the ball went inside the ring without touching the rim), partially failed (i.e., the ball did not go in the ring but hit the rim), or completely failed (i.e., the ball missed the ring). In the virtual AR setup, these scores also changed the ring color from white to green (for one point), or yellow (for half a point), to red (for no points) (Figure 3).

We then used the following learning algorithm 1 based on the optimal functional task difficulty framework in the motor skill learning literature by Guadagnoli et al. [26] to determine when to adapt the task difficulty based on the performance score:

Algorithm 1 Pseudocode: Adaptive Learning Algorithm

```
Initialize at the lowest task difficulty
while task difficulty ≠ highest do
    (1) Assess Learner's Performance                              ▷ By measuring score
    if attempt == true then
        score = 1, ring = green                                   ▷ if attempt = success
        score = 0.5, ring = yellow                        ▷ if attempt = partial success
        score = 0, ring = red                                      ▷ if attempt = failed

    (2) Check if the Training is at the Optimal Challenge Point
    Calculate the running average (denoted as running_average) of the score over
4 attempts
    Calculate the current derivative of the running average

    (3) Update task difficulty                                 ▷ By adapting the tool
    if derivative == 0 then                        ▷ i.e. running average plateaued
        if running_average ≥ 0.5 then
            increase task difficulty → by adapting harder (decrease ring dia. by
10%)
        else if running_average ≤ 0.25 then
            decrease task difficulty → by adapting easier (increase ring dia. by 10%)
        else
            maintain task difficulty → no adaptation
    Repeat steps (1) (2) and (3) until task difficulty = highest
```

These points were used change the functional task difficulty by increasing or decreasing the virtual ring's diameter. To prevent the ring diameter from changing after each attempt, a running average with a window size of 4 was used (Equation 1). The window size was determined based on observations from our pilot study that showed that a smaller window could cause constant adaptations due to outlier data points, whereas a larger window would result in slower adaptations and longer durations of score plateauing.

$$\bar{r}_{\text{avg}} = \frac{s_m + s_{m-1} + \cdots + s_{m-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} s_{m-i}. \quad (1)$$

$$d_m = r_{\text{avg(m)}} - r_{\text{avg(m-1)}} \quad (2)$$

To determine if performance was plateauing at a given difficulty level, and thus the task difficulty needed to change, we computed the derivative of the running average (Equation 2) on every attempt, after the completion of the first two running average windows. If the performance had plateaued (i.e., the derivative was zero), we then assessed if the running average indicated that the task was too easy ($\mu >= 0.5$) or too hard ($\mu =< 0.25$). If the task was too easy we decreased the diameter of the ring by 10%, if the task was too hard we increased the diameter by 10%, otherwise, the task difficulty was maintained and the ring diameter did not change. By adapting the ring diameter so that the task was neither too easy (where the participant consistently scored high) nor too difficult (where the participant consistently scored low) and we could maintain the optimal challenge point at which learning would be the highest.

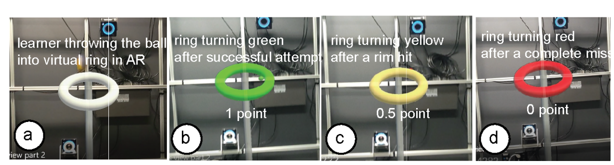


Figure 3: (a) In the virtual AR setup, these scores also changed the ring color from white to (b) green (for one point), or (c) yellow (for half a point), to (d) red (for no points).

3.5 Study Environment and Apparatus

We conducted the experiment within a room containing a 9' x 9' metal frame mounted with twenty-two Optitrack[3] cameras (Figure 1a). Note that while we used an external OptiTrack setup, in time we imagine inside-out tracking on an HMD could provide this sensing capability, removing the need for a specialized environment and expensive tracking system.

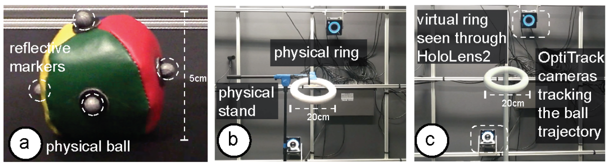


Figure 4: The study system components: (a) the 5 centimeter diameter physical ball, (b) the 20 centimeter diameter physical ring mounted on a physical stand, (c) the 20 centimeter diameter virtual ring as seen through the HoloLens 2.

For the control (non-adaptive physical) training conditions and the assessment tests, a physical Styrofoam ring with an inner diameter of 20 cm was placed 1.5 meters from a dedicated throwing location on the floor. The ring was mounted on a stand 1.2 meters above the ground and tilted at a 45 degree angle. This distance was based on the maximum interaction volume possible without losing tracking accuracy.

For the AR-based training conditions, participants viewed a 20-centimeter diameter virtual ring with HoloLens2 that was a holographic replica (mimicked the color and shape) of the physical ring. We overlapped the positions and orientations of the virtual-AR and the physical ring for target consistency throughout the study. We placed retro-reflective markers on HoloLens2 and the physical ball for tracking their positions with respect to the participant using Optitrack. We then coincided the physical space coordinates with the virtual space in Unity3D using common origin points.

Throughout the study, participants were asked to throw a soft leather juggling-style ball of 5 cm in diameter (Fig 1-a). We used a soft juggling ball rather than a rubber or plastic ball to avoid damaging the Optitrack cameras and to buffer any miscalibration resulting from the ball hitting the frame. We tracked the rotation and trajectory of the ball using six retro-reflective 3mm markers affixed to the ball. We implemented the realtime tracking using Motive3 and Unity3D.

3.6 Procedure and Study Design

The study employed a between-subjects design, where participants were placed into one of two groups. Group A completed a control (non-adaptive physical) training condition and a non-adaptive AR training condition. Group B completed a control (non-adaptive physical) training condition and an adaptive AR training condition. We used the non-adaptive physical training condition as our control condition to compare the learning gains for the AR training. In the control (non-adaptive physical) training condition, participants attempted 60 throws at the *physical* ring. The difficulty of the task (i.e., the diameter of the ring) did not change. During the training conditions, participants attempted 60 throws at a *virtual* ring. For non-adaptive AR training condition, the difficulty of the task (i.e., the diameter of the ring) also did not change. In the adaptive AR training condition the ring changed diameter based on the adaptive task difficulty algorithm described in this section.

[3]OptiTrack - Prime 22, https://optitrack.com/cameras/primex-22/

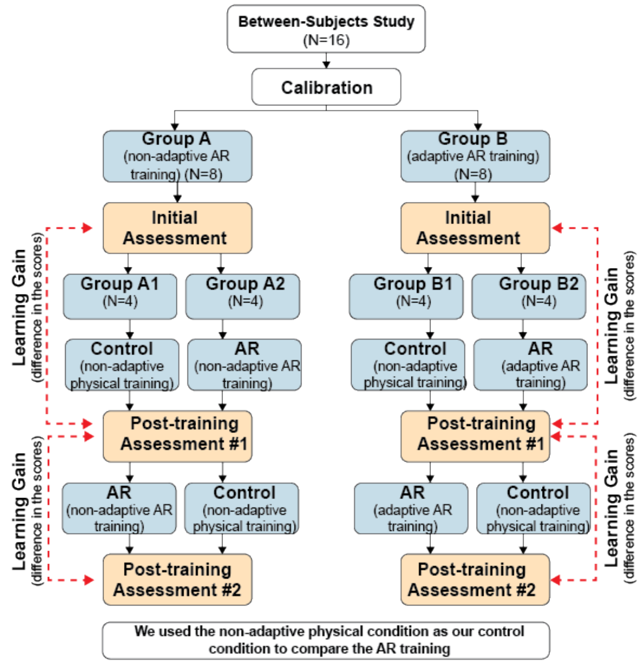


Figure 5: The study employed a between-subjects design, where participants (n=16) were placed into one of two groups. Group A completed a control (non-adaptive physical) training condition and a non-adaptive AR training condition. Group B completed a control (non-adaptive physical) training condition and an adaptive AR training condition.

Each participant started with short calibration step where they performed an underhand and overhand throw at the physical and the AR ring to familiarize themselves with the experimental setup. After the calibration step and before any training conditions, participants performed an initial assessment test where they attempted 20 throws at the physical ring. Then they completed one of their two training conditions with 60 throws followed by a second assessment test, with another 20 throws at the physical ring. They then completed the second training condition of 60 throws followed by a third assessment test of 20 throws. Across both groups, the order of the control (non-adaptive physical) and AR (adaptive or non-adaptive) training conditions was counterbalanced to mitigate learning effects.

During the experiment, participants were instructed to score as many points as possible. To avoid fatigue, participants took a mandatory 5-minute break after each condition and assessment test, in addition to voluntary breaks whenever they experienced tiredness. The study took approximately 1 hour to complete with

Study Stages	Number of Throws
initial assessment test	20
training condition #1	60
post-training test #1	20
training condition #2	60
post-training test #2	20
total attempts	180

Table 1: Every participant attempted a total of 180 throws during the study through the above stages.

each participant attempting 180 throws.[4] We recorded the ball trajectory and rotation, timestamped video of the participants' view through the HoloLens, and their performance score per attempt. We also recorded their verbal comments during the study and feedback using our questionnaire. Finally, we collected qualitative feedback through pre-study and post-study questionnaires.

To analyze participant feedback, we first transcribed the interview video feedback and combined it with the feedback collected through the post-study questionnaires. Then, two members of the research team conducted a thematic analysis to identify emerging themes. Two rounds of coding were performed and the inter-rater reliability was over 80% [39, 60].

4 RESULTS

4.1 Learning Gains

To understand the impact of adapting the functional task difficulty using virtual training tools in AR on the learning gains compared to non-adaptive virtual training tools, we computed the performance score difference between the first and second assessments and the second and third assessments. The average performance score difference when using the non-adaptive AR condition was lower (μ = -0.19 points, σ = 1.94) than when using the adaptive AR condition (μ = 0.63 points, σ = 0.53), with ANOVA showing no significant difference between these conditions (p = 0.05; Figure 6). However, the slightly higher score for adaptive AR training suggests that adapting the functional task difficulty in AR can potentially lead to higher learning gains compared to non-adaptive AR training.

We also performed **a weighted ANOVA** to account for unequal datapoints between the three groups (as the datapoints for physical training were twice as the other two test groups). The results indicated no statistically significant group differences, with an **$F(2, 29) = 0.337$ and $p = 0.717$**. To further explore potential pairwise differences, we conducted an unweighted Tukey Honest Significant Difference (HSD) post-hoc test shown in table 2. The test revealed no significant differences between any group pairs.

Group 1	Group 2	Mean Diff	P-adj	Significant
Adaptive AR	Nonadaptive AR	0.9375	0.4774	False
Adaptive AR	Physical	0.0625	0.9967	False
Non-adaptive AR	Physical	-0.875	0.4024	False

Table 2: Unweighted Tukey Honest Significant Difference (HSD) post-hoc test results to study the pairwise differences

[4]As in prior published work, this method is designed to compensate for variations in participants' stamina, fitness, and skill levels by allowing the participants to take as much time and as many breaks as they needed to complete the throws, in addition to mandatory breaks.

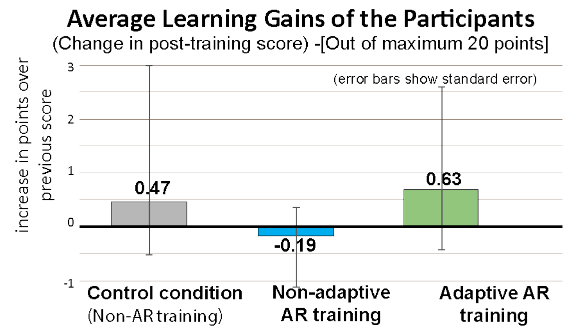
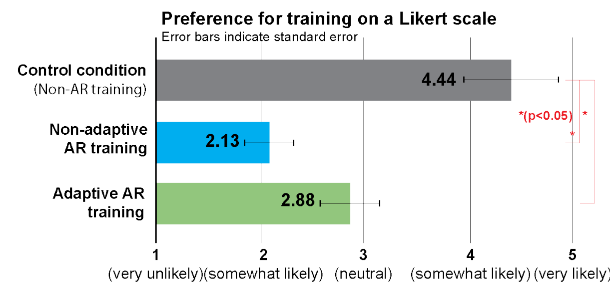


Figure 6: The average performance score difference for the baseline, non-adaptive AR training, and adaptive AR training. Error bars depict the standard deviation. The error bars depict the standard error.



Experience of training [on a Likert scale from 1(strongly agree) to 5 (strongly disagree)]	Experienced Tiredness	Experienced Boredom	Experienced Engagement	Experienced Motivation	Ease of Learning	Faster Learning
	qn: I felt tired during the training	qn:I felt bored during the training	qn:I felt engaged while training	qn:I felt motivated while training	qn:I felt the learning was easy	qn:I felt the learning was fast
Control condition (Non-AR training)	3.75	4.06	1.81	1.94	1.88	1.88
Non-adaptive AR training	3.25	3.25	2.75	2.75	3.25*	3.50*
Adaptive AR training	3.25	3.05	3.00*	3.38*	3.5*	3.50*

*(p<0.05)

Figure 7: (top)Bar chart showing the median ratings for the baseline, adaptive, and non-adaptive conditions. (bottom) A table showing the average score on a 5-point Likert scale describing their feedback on the experience of training on each of the three conditions along the dimensions of tiredness, boredom, engagement, motivation, ease of learning, and pace of learning. The error bars depict the standard error.

4.2 Learning Experience

While the participants reported a slightly higher preference for the adaptive condition (Mdn = 2.88, σ = 1.25) compared to the non-adaptive condition (Mdn = 2.13, σ = 1.25), they reported a significantly higher preference for the baseline condition (Mdn = 4.44, σ = 0.62) compared to both AR conditions (p = 0.05) (Figure 6-left). We observed similar trends in ratings of training experience for factors of: cognitive load (i.e., feeling tired and bored), excitement (i.e., feeling engaged and motivated), and learning (i.e., ease and pace of learning). When asked about the reasons for their preferences, participants stated that the baseline condition was *"more* *real"* (P6), *"blended well with the environment"* (P14), and made them feel *"comfortable [...] because it is exactly how [they] expect the ball to behave while throwing it"* (P1).

Study Limitation: Our study employed a between-participants design to avoid learning or transfer effects between adaptive and non-adaptive AR conditions. While this helped isolate the effects of each condition, it limited our ability to compare individual performance across conditions and required a larger sample size to account for inter-individual variability. Differences in prior experience, spatial reasoning, or familiarity with AR technology may also have influenced outcomes. A within-participants design could allow for more direct comparison and better control of individual differences.

In summary, the results addressing **RQ1** suggest that there may be a trend towards improved performance and increased preference for adaptive AR, but further investigation is needed to establish statistical significance. Additionally, the significantly higher preference for the baseline condition over both the AR conditions underscores the need to further study the impact and complexities of designing adaptation strategies for AR training tools in the same way as physical adaptive training tools. We examine this in the next section.

4.3 Design Insights for AR Adaptive Training

We collected feedback on participants' training experiences via an open-ended questionnaire and categorized their feedback along the following themes that point to the design challenges in leveraging AR affordances for adapting functional task difficulty.

4.3.1 Limited Visual Cues Affecting the Depth Perception. Participants reported relying on environmental visual cues, such as shadows and object occlusions, for depth perception during training, for example when planning throws, judging ring distance, and verifying that the ball had passed through the ring. In the baseline condition, *"blending with the environment and appropriate depth perception"* (P13) facilitated learning. In contrast, the AR conditions lacked these cues, making depth harder to judge. P8 noted difficulty perceiving *"virtual depth felt harder to perceive and understand where it [the system] thinks the ball hit the rim"*, while adaptive AR further complicated depth perception, with ring size changes sometimes misinterpreted as distance shifts. P9 reported feeling no improvement due to poor depth perception, and P10 found *"visualization didn't help me understand where the ring was or if the ball went in"*. Participants suggested adding visual and auditory feedback to address these issues (P12). This highlights the design challenge of synchronizing elements like shadows and occlusion with AR tool adaptations for better depth perception.

4.3.2 Limited Cues Affecting Performance Assessment. Our analysis highlighted the critical role of environmental cues – visual, auditory, and multimodal – in motor skill learning. These cues that result from the interaction between objects and the environment were important to participants when assessing their performance and updating their strategy for the action. Participants relied on these cues to assess performance and refine their strategies. For example, P11 noted that *"in the real condition, feedback from seeing the rim distorted after being hit by the ball, the sound of the ball when it hit the rim, and following the ball trajectory were helpful, none of these were present in the AR condition"*. Similarly, auditory and vibration cues indicated if the ball was thrown with excessive force or too far, which were lacking in AR. Limited visual feedback (e.g., ring color changes) and the absence of cues from the physical ball interacting with the virtual rim hindered error-based learning and strategy adjustment. P14 observed that *"as true for any physical entity, the visual cues such as shaking when hit on the rim and auditory feedback were information on the outcomes of the throw trial, the non-adaptive AR mode lacked the aforementioned, leading to frequent misjudgments of the throw"*. Participants also cited how *"the lack of 'the auditory feedback when the ball hit the ring' in the non-adaptive AR mode hindered the learning process"* (P13), and made the experience seem unreal, e.g., *"I couldn't get the voice feedback in AR (e.g., hitting the rim), the feeling was not real"* (P12). This reveals the design challenge of simulating realistic interactions between AR and physical objects, which is harder than simulating interactions between multiple AR objects.

4.3.3 AR Training Affecting Skill-transfer to Physical Environments. Participants' unfamiliarity with AR, (in both adaptive and non-adaptive AR conditions) made them feel as though they were learning a new task, hindering skill transfer during assessment condition which was on a non-AR setup. P6 noted being *"more used to the non-AR mode,"* while P1 found it challenging to mentally align the real ball with the AR ring, as *"the non-AR mode was consistent with real-world expectations."* Similarly, P5 described AR as a *"learning experience"* where they questioned AR's physical rules instead of focusing solely on the motor skill, unlike the physical condition where established physics were intuitive. This highlights a design challenge: learning unfamiliar environmental affordances adds task difficulty.

These themes address **RQ2**, highlighting subtle discrepancies between real-world and augmented tasks. They reveal that designing adaptive AR tools demands a distinct approach compared to physical tools. We discuss this in detail in the next section.

5 DISCUSSION

The results of our exploratory study indicate that designing adaptive AR training tools requires a careful consideration of the interactions between the learner, physical objects, virtual AR objects, and the learning environment. This section explores some design and research opportunities for adapting functional task difficulty using AR, considering current and future AR capabilities.

5.1 Current Opportunities - Adapting Simple AR Overlays

Despite the limitations of current technology in sensing contextual information, capturing the full-range of nuanced interactions, and simulating realistic adaptations, we see design opportunities for adapting functional task difficulty using AR-visualization overlays, such as text or graphic markers superimposed on physical tools and environments. For instance, in sports training, virtual markers could guide players by superimposing targets on the field, guiding players to aim at specific locations. Adjusting marker placement can allow adaptive training for skill enhancement. We observe this method has been used in 2D AR for aiding mobility in disabled children [49], but its application in 3D immersive AR remains unexplored. Similarly, AR visualization overlays could be used to provide support during a task. For example, overlays providing static cues [14] such as virtual markers or annotations, and dynamic cues [17] such as animations, simulations, or interactive virtual 3D models, can be used to guide learners' actions, provide additional information about task planning, or highlight critical areas of focus during task execution. These static and dynamic visualization overlays can be adjusted in real-time based on the learner's performance, allowing for adaptive and personalized support provided to the learner that can be adjusted as the learner improves their skill level.

Another aspect to consider that may influence dissonance in depth perception, self-assessment, and skill transfer could be the vergence-accommodation conflict (VAC), which sometimes occurs in AR systems because of a discrepancy between the inward/outward rotation of the eyes (vergence) and the eye's focus on the AR screen (accommodation) [8]. While some research has shown that VAC can hinder visual performance and cause visual fatigue [27], the recent advances that resolve VAC in HMDs [35] offer the opportunity to study the limiting effects of VAC specifically in the context of motor-skill learning and incorporate the insights while designing adaption.

5.2 Near Future Opportunities - Adapting Multimodal Cues and Realism

As advances in tracking, depth sensing, and spatial mapping enable precise AR object placement and progress in graphics, physics, and object recognition enhances realism, more design possibilities open up to adapt the functional task difficulty through multimodal cues. Our insights on how learners rely on interaction cues for task execution, planning, and performance assessment give directions for adapting multimodal cues. *Spatial* cues that impact depth and distance perception, *sensory* cues that provide visual and auditory information, and *temporal* cues that provide information about the speed and the time of interaction can all be adapted in interesting ways. For example, in a virtual assembly task, the perception of depth cues can be adapted to increase or decrease the perceived distance between objects and adapt the functional task difficulty based on learners' task precision. Or, in a surgical simulation, the auditory cues representing the sound of a successful incision can be intensified or attenuated to make the task easier as per the learner's abilities and optimize the feedback support. Likewise, in a basketball shooting training scenario, the speed at which the feedback on shot accuracy and trajectory can be adjusted as increasing the speed raises the task difficulty level because the learner needs to make quicker adjustments to react.

5.3 Future Opportunities - Adapting Perception:

As AR technologies advance further, designers will gain additional opportunities to fine-tune AR cues to intentionally manipulate realism to change the functional task difficulty. An example of this manipulation would be to selectively 'mute' certain visual, spatial, and multimodal cues associated with the task while keeping all others stable. For example, the system could simulate a basketball hoop that functions exactly as a real hoop would, but mute the sound of the ball and hoop interacting, or the shake of the hoop when impacted by the ball, or some other individual cue. This manipulation of realism may allow learners to rely less on particular cues and develop greater expertise in motor skills as a result. Another speculative idea could be to reimagine how objects in a motor skill task could be altered in creative ways. For example, imagine an illuminated transparent physical ball thrown at a target that switches off once the ball is thrown and a virtual ball in AR is shown in replacement to the user in slow motion to depict their throw trajectory. As the learners gain a better understanding of the task, the speed of the AR ball can be adjusted accordingly.

These design prospects expand the design space for AR tools for personalized motor skill learning through adaptation of functional task difficulty, and we hope that these ideas can form an initial road map for further research in this space.

6 LIMITATIONS AND FUTURE WORK

While our exploratory study revealed insights into the design of AR adaptive training tools, we acknowledge it has limitations which should be addressed in future work. We focused on specific ball-throwing tasks which may limit the generalizability of our results to other complex motor skills. Building and evaluating AR adaptive training tools for additional motor skills could give a richer picture of the challenges and opportunities in this space. We also acknowledge that a single-session study may miss important aspects of motor skill learning. Examining long-term skill acquisition through longitudinal studies with more participants is important to gain a comprehensive picture of AR's impact on motor skill learning. It is also noteworthy that extended use of AR head-mounted devices can lead to discomfort and distraction and it is important to consider user comfort and ergonomics in tool design.

Informed by our insights, we are currently developing a design framework for adaptive AR learning which will be evaluated by building and testing varied study prototypes for adaptive training tools in AR (starting from the insights in Section 5.1). We also plan to explore the combination of our adaptive functional task approach with established instruction and feedback techniques, as we believe adaptive multimodal guidance in conjunction with task difficulty adjustment could enhance AR's effectiveness for motor skill learning. Finally, in this work we limited our scope to AR tools, but the insights gained from our study could inform future research on adaptive tools in Virtual Reality as well.

7 CONCLUSION

In conclusion, this work fills a gap in research by exploring the use of augmented reality to design adaptive tools adjusting functional task difficulty during motor skill training. Through a user study, we uncovered a novel set of challenges in designing adaptive AR training tools, concluding that existing methods for physical tools may not apply directly to AR. Our findings suggest new design opportunities, such as adjusting visualization targets, spatial cues, sensory cues, temporal cues, and realism manipulation. Together, this research reveals the path forward for future investigations into motor skill training techniques enabled by augmented reality.

ACKNOWLEDGMENTS

We thank Jared Braun and Olivia Edgington for their valuable contributions to the project.

REFERENCES

[1] ZA Abbas and Jamie S North. 2018. Good-vs. poor-trial feedback in motor learning: The role of self-efficacy and intrinsic motivation across levels of task difficulty. *Journal of Learning and Instruction* 55 (2018), 105–112. https://doi.org/10.1016/j.learninstruc.2017.09.009

[2] Jack A Adams. 1971. A closed-loop theory of motor learning. *Journal of motor behavior* 3, 2 (1971), 111–150. https://doi.org/10.1080/00222895.1971.10734898

[3] Rajwa Al-Hrathi, Ali Karime, Hussein Al-Osman, and Abdulmotaleb El Saddik. 2012. Exerlearn Bike: An Exergaming System for Children's Educational and Physical Well-Being. In *2012 IEEE International Conference on Multimedia and Expo Workshops*. 489–494. https://doi.org/10.1109/ICMEW.2012.91

[4] Fraser Anderson, Tovi Grossman, Justin Matejka, and George Fitzmaurice. 2013. YouMove: Enhancing Movement Training with an Augmented Reality Mirror. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology* (St. Andrews, Scotland, United Kingdom) *(UIST '13)*. Association for Computing Machinery, New York, NY, USA, 311–320. https://doi.org/10.1145/2501988.2502045

[5] Hippokratis Apostolidis, Nikolaos Politopoulos, Panagiotis Stylianidis, Agisilaos Chaldogeridis, Nikolaos Stavropoulos, and Thrasyvoulos Tsiatsos. 2018. Instructional mirroring applied in basketball shooting technique. In *Interactive Mobile Communication Technologies and Learning: Proceedings of the 11th IMCL Conference*. Springer, 603–611.

[6] Stephanie Arevalo Arboleda, Franziska Rücker, Tim Dierks, and Jens Gerken. 2021. Assisting Manipulation and Grasping in Robot Teleoperation with Augmented Reality Visual Cues. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 728, 14 pages. https://doi.org/10.1145/3411764.3445398

[7] UH Ariffin, NAM Mokmin, and MA Akmal. 2022. Augmented reality technology in physical education: A systematic review in instructional design, and AR implementation option over the last 5 years. *Advanced Journal of Technical and Vocational Education* 6, 1 (2022), 13–20.

[8] Steve Aukstakalnis. 2016. *Practical augmented reality: A guide to the technologies, applications, and human factors for AR and VR*. Addison-Wesley Professional.

[9] Yee Mon Aung and Adel Al-Jumaily. 2011. Rehabilitation exercise with real-time muscle simulation based EMG and AR. In *2011 11th International Conference on Hybrid Intelligent Systems (HIS)*. IEEE, 641–646.

[10] Patrick Baudisch, Henning Pohl, Stefanie Reinicke, Emilia Wittmers, Patrick Lühne, Marius Knaust, Sven Köhler, Patrick Schmidt, and Christian Holz. 2014. Imaginary reality basketball: A ball game without a ball. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems*. 575–578.

[11] James Baumeister, Seung Youb Ssin, Neven AM ElSayed, Jillian Dorrian, David P Webb, James A Walsh, Timothy M Simon, Andrew Irlitti, Ross T Smith, Mark Kohler, et al. 2017. Cognitive cost of using augmented reality displays. *IEEE transactions on visualization and computer graphics* 23, 11 (2017), 2378–2388.

[12] Tim Bosch, Gu van Rhijn, Frank Krause, Reinier Könemann, Ellen S. Wilschut, and Michiel de Looze. 2020. Spatial Augmented Reality: A Tool for Operator Guidance and Training Evaluated in Five Industrial Case Studies. In *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments* (Corfu, Greece) *(PETRA '20)*. Association for Computing Machinery, New York, NY, USA, Article 40, 7 pages. https://doi.org/10.1145/3389189.3397975

[13] Kuo-En Chang, Jia Zhang, Yang-Sheng Huang, Tzu-Chien Liu, and Yao-Ting Sung. 2020. Applying augmented reality in physical education on motor skills learning. *Interactive Learning Environments* 28, 6 (2020), 685–697.

[14] Jean-Rémy Chardonnet, Guillaume Fromentin, and José Outeiro. 2017. Augmented reality as an aid for the use of machine tools. *Res. & Sci. Today* 13 (2017), 25.

[15] Wojciech B Cieślński, Janusz Sobecki, Paweł A Piepiora, Zbigniew N Piepiora, and Kazimierz Witkowski. 2016. Application of the Augmented Reality in prototyping the educational simulator in sport-the example of judo. In *Journal of Physics: Conference Series*, Vol. 710. IOP Publishing, 012016.

[16] Dav Clark and Richard B Ivry. 2010. Multiple systems for motor skill learning. *Wiley Interdisciplinary Reviews: Cognitive Science* 1, 4 (2010), 461–467.

[17] Alysson Messias da Silva, SG Gustavo, and Francisco Petrônio Alencar de Medeiros. 2021. A Review on Augmented Reality Applied to Sports. In *2021 16th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE, 1–6.

[18] Florian Daiber, Felix Kosmalla, and Antonio Krüger. 2013. BouldAR: using augmented reality to support collaborative boulder training. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. 949–954.

[19] Iwan de Kok, Julian Hough, Felix Hülsmann, Mario Botsch, David Schlangen, and Stefan Kopp. 2015. A Multimodal System for Real-Time Action Instruction in Motor Skill Learning. In *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction* (Seattle, Washington, USA) *(ICMI '15)*. Association for Computing Machinery, New York, NY, USA, 355–362. https://doi.org/10.1145/2818346.2820746

[20] Alessandro De Mauro, Belinda Lange, and Andreas Dünser. 2014. Advanced user interfaces for neurorehabilitation.

[21] Alena Denisova and Paul Cairns. 2015. Adaptation in digital games: the effect of challenge adjustment on player performance and experience. In *Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play*. 97–101.

[22] William H Edwards. 2010. *Motor learning and control: From theory to practice*. Cengage Learning.

[23] Peter Eisert, Jurgen Rurainsky, and Philipp Fechteler. 2007. Virtual mirror: Real-time tracking of shoes in augmented reality environments. In *2007 IEEE International Conference on Image Processing*, Vol. 2. IEEE, II–557.

[24] Paul M Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology* 47, 6 (1954), 381. https://doi.org/10.1037/h0055392

[25] Stefan Gradl, Bjoern M Eskofier, Dominic Eskofier, Christopher Mutschler, and Stephan Otto. 2016. Virtual and augmented reality in sports: an overview and acceptance study. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. 885–888.

[26] Mark A Guadagnoli and Timothy D Lee. 2004. Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. *Journal of motor behavior* 36, 2 (2004), 212–224. https://doi.org/10.3200/JMBR.36.2.212-224

[27] David M Hoffman, Ahna R Girshick, Kurt Akeley, and Martin S Banks. 2008. Vergence–accommodation conflicts hinder visual performance and cause visual fatigue. *Journal of vision* 8, 3 (2008), 33–33.

[28] Gaoping Huang, Xun Qian, Tianyi Wang, Fagun Patel, Maitreya Sreeram, Yuanzhi Cao, Karthik Ramani, and Alexander J. Quinn. 2021. AdapTutAR: An Adaptive Tutoring System for Machine Tasks in Augmented Reality. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 417, 15 pages. https://doi.org/10.1145/3411764.3445283

[29] Tony Jebara, Cyrus Eyster, Joshua Weaver, Thad Starner, and Alex Pentland. 1997. Stochasticks: Augmenting the billiards experience with probabilistic vision and wearable computers. In *Digest of Papers. First International Symposium on Wearable Computers*. IEEE, 138–145.

[30] Raine Kajastila, Leo Holsti, and Perttu Hämäläinen. 2016. The augmented climbing wall: High-exertion proximity interaction on a wall-sized interactive surface. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 758–769.

[31] Viktor Kálmán, Csaba Baczó, Makis Livadas, and Tamás Csielka. 2015. Wearable technology to help with visual challenges–two case studies. In *Assistive technology*. IOS Press, 526–532.

[32] Charles R Kelley. 1969. What is adaptive training? *Human Factors* 11, 6 (1969), 547–556. https://doi.org/10.1177/001872086901100602

[33] Philip Kelly and Noel E O'Connor. 2012. Visualisation of tennis swings for coaching. In *2012 13th International Workshop on Image Analysis for Multimedia Interactive Services*. IEEE, 1–4.

[34] Robert Kerr and Bernard Booth. 1978. Specific and varied practice of motor skill. *Journal of Perceptual and motor skills* 46, 2 (1978), 395–401. https://doi.org/10.1177/003151257804600201

[35] Gregory Kramida. 2015. Resolving the vergence-accommodation conflict in head-mounted displays. *IEEE transactions on visualization and computer graphics* 22, 7 (2015), 1912–1931.

[36] Itaru Kuramoto, Yukari Nishimura, Keiko Yamamoto, Yu Shibuya, and Yoshihiro Tsujino. 2013. Visualizing velocity and acceleration on augmented practice mirror self-learning support system of physical motion. In *2013 Second IIAI International Conference on Advanced Applied Informatics*. IEEE, 365–368.

[37] Dwi Ely Kurniawan, Parulian Silalahi, and Adelia Pratiwi. 2019. ARtrace: Augmented Reality for Student's Fine Motor Learning. In *2019 2nd International Conference on Applied Engineering (ICAE)*. IEEE, 1–5.

[38] Tica Lin, Rishi Singh, Yalong Yang, Carolina Nobre, Johanna Beyer, Maurice A Smith, and Hanspeter Pfister. 2021. Towards an understanding of situated ar visualization for basketball free-throw training. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–13.

[39] Yvonna S Lincoln and Egon G Guba. 1985. *Naturalistic inquiry*. sage.

[40] Danica Mast, Michel Bosman, Sylvia Schipper, and Sanne de Vries. 2017. BalanSAR: Using spatial augmented reality to train children's balancing skills in physical education. In *Proceedings of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction*. 625–631.

[41] Helen C Miles, Serban R Pop, Simon J Watt, Gavin P Lawrence, and Nigel W John. 2012. A review of virtual environments for training in ball sports. *Computers & Graphics* 36, 6 (2012), 714–726.

[42] Maria F Montoya, John E Muñoz, and Oscar A Henao. 2020. Enhancing virtual rehabilitation in upper limbs with biocybernetic adaptation: the effects of virtual reality on perceived muscle fatigue, game performance and user experience. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28, 3 (2020), 740–747.

[43] Antonio-José Moreno-Guerrero, Santiago Alonso García, Magdalena Ramos Navas-Parejo, María Natalia Campos-Soto, and Gerardo Gómez García. 2020. Augmented reality as a resource for improving learning in the physical education classroom. *International journal of environmental research and public health* 17, 10 (2020), 3637.

[44] Karl M Newell, Yeou-Teh Liu, and Gottfried Mayer-Kress. 2001. Time scales in motor learning and development. *Journal of Psychological review* 108, 1 (2001), 57. https://doi.org/10.1037/0033-295X.108.1.57

[45] Jun Nishida, Yudai Tanaka, Romain Nith, and Pedro Lopes. 2022. DigituSync: A Dual-User Passive Exoskeleton Glove That Adaptively Shares Hand Gestures. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. 1–12.

[46] Mitchell Page and Andrew Vande Moere. 2007. Evaluating a wearable display jersey for augmenting team sports awareness. In *Pervasive Computing: 5th International Conference, PERVASIVE 2007, Toronto, Canada, May 13-16, 2007. Proceedings 5*. Springer, 91–108.

[47] Hyung Kun Park and Woohun Lee. 2016. Motion Echo Snowboard: Enhancing Body Movement Perception in Sport via Visually Augmented Feedback. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems (DIS'16)*. 192–203. https://doi.org/10.1145/2901790.2901797

[48] Miguel Portaz, Raúl Cabestrero, Pilar Quirós, and Olga C Santos. 2024. AI-Powered Psychomotor Learning Through Basketball Practice: Opportunities and Challenges. *Mind, Body, and Digital Brains* (2024), 193–215.

[49] Emmanuelle Richard, Valérie Billaudeau, Paul Richard, and Gilles Gaudin. 2007. Augmented reality for rehabilitation of cognitive disabled children: A preliminary study. In *2007 virtual rehabilitation*. IEEE, 102–108.

[50] Sandro Ropelato, Marino Menozzi, Dominique Michel, and Michael Siegrist. 2020. Augmented reality microsurgery: a tool for training micromanipulations in ophthalmic surgery using augmented reality. *Simulation in Healthcare* 15, 2 (2020), 122–127.

[51] Alan W Salmoni, Richard A Schmidt, and Charles B Walter. 1984. Knowledge of results and motor learning: a review and critical reappraisal. *Journal of Psychological bulletin* 95, 3 (1984), 355. https://doi.org/10.1037/0033-2909.95.3.355

[52] Yuji Sano, Koya Sato, Ryoichiro Shiraishi, and Mai Otsuki. 2016. Sports support system: Augmented ball game for filling gap between player skill levels. In *Proceedings of the 2016 ACM International Conference on Interactive Surfaces and Spaces*. 361–366.

[53] Richard A Schmidt. 1975. A schema theory of discrete motor skill learning. *Journal of Psychological review* 82, 4 (1975), 225. https://doi.org/10.1037/H0076770

[54] Richard A Schmidt. 1991. Frequent augmented feedback can degrade learning: Evidence and interpretations. In *Tutorials in motor neuroscience*. Springer, 59–75.

[55] Isabelle M Shuggi, Hyuk Oh, Patricia A Shewokis, and Rodolphe J Gentili. 2017. Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. *Journal of Neuroscience* 360 (2017), 166–179. https://doi.org/10.1016/j.neuroscience.2017.07.048

[56] Cezary Sieluzycki, Patryk Kaczmarczyk, Janusz Sobecki, Kazimierz Witkowski, Jarosław Maśliński, and Wojciech Cieśliński. 2016. Microsoft Kinect as a tool to support training in professional sports: augmented reality application to Tachi-Waza techniques in judo. In *2016 Third European Network Intelligence Conference (ENIC)*. IEEE, 153–158.

[57] Rajinder Sodhi, Hrvoje Benko, and Andrew Wilson. 2012. LightGuide: projected visualizations for hand movement guidance. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 179–188.

[58] Pooya Soltani and Antoine HP Morice. 2020. Augmented reality tools for sports education and training. *Computers & Education* 155 (2020), 103923.

[59] Gábor Sörös, Florian Daiber, and Tomer Weller. 2013. Cyclo: a personal bike coach through the glass. In *SIGGRAPH Asia 2013 Symposium on Mobile Graphics and Interactive Applications*. 1–4.

[60] Sharon Spall. 1998. Peer debriefing in qualitative research: Emerging operational models. *Qualitative inquiry* 4, 2 (1998), 280–292.

[61] Masayasu Sumiya, Wataru Yamada, and Keiichi Ochiai. 2022. Anywhere Hoop: Virtual Free Throw Training System. In *Adjunct Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. 1–3.

[62] Feng Sun and Chao Zheng. 2021. The application of basketball technology multimedia computer-assisted instruction courseware in physical education. *The International Journal of Electrical Engineering & Education* (2021), 00207209211013440.

[63] Emanuel Todorov, Reza Shadmehr, and Emilio Bizzi. 1997. Augmented feedback presented in a virtual environment accelerates learning of a difficult motor task. *Journal of motor behavior* 29, 2 (1997), 147–158.

[64] Dishita G Turakhia, Yini Qi, Lotta-Gili Blumberg, Andrew Wong, and Stefanie Mueller. 2021. Can Physical Tools that Adapt their Shape based on a Learner's Performance Help in Motor Skill Training?. In *Proceedings of the Fifteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–12.

[65] Dishita G Turakhia, Andrew Wong, Yini Qi, Lotta-Gili Blumberg, Yoonji Kim, and Stefanie Mueller. 2021. Adapt2Learn: A Toolkit for Configuring the Learning Algorithm for Adaptive Physical Tools for Motor-Skill Learning. In *Designing Interactive Systems Conference 2021*. 1301–1312.

[66] Jaakko Vuorio. 2024. Studying the Use of Virtual Reality Learning Environments to Engage School Children in Safe Cycling Education. *Simulation & Gaming* 55, 3 (2024), 418–441. https://doi.org/10.1177/10468781241246566 arXiv:https://doi.org/10.1177/10468781241246566

[67] Frederik Wiehr, Felix Kosmalla, Florian Daiber, and Antonio Krüger. 2016. betaCube: Enhancing training for climbing by a self-calibrating camera-projection unit. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. 1998–2004.

[68] Gabriele Wulf, Charles Shea, and Rebecca Lewthwaite. 2010. Motor skill learning and performance: a review of influential factors. *Journal of Medical education* 44, 1 (2010), 75–84. https://doi.org/10.1111/j.1365-2923.2009.03421.x

[69] Junichi Yamaoka and Yasuaki Kakehi. 2013. dePENd: augmented handwriting system using ferromagnetism of a ballpoint pen. In *Proceedings of the 26th annual ACM symposium on User interface software and technology (UIST'13)*. 203–210. https://doi.org/10.1145/2501988.2502017